Strategic Uncertainty, Competition and Asymmetric Pass-Through

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Abstract

Prices adjust more slowly and incompletely to cost decreases than to increases. Although pervasive, identifying the underlying cause of asymmetric pass-through is challenging. I document such asymmetry in an empirical setting where conventional consumer-side explanations are absent, suggesting that it can arise from strategic interactions among suppliers. Using electricity market bidding data and a design suited for testing asymmetry, I show that firms adopt different strategies following cost decreases. Structural estimation of firms' beliefs about competitors' strategies reveals that beliefs also differ by cost-change direction, with greater dispersion when costs decrease, contributing to incomplete price adjustment to downward cost changes.

JEL codes: D44, D22, D43, L11, L13

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1 Introduction

Asymmetric price response to cost change, a specific form of downward price rigidity often termed the rockets-and-feathers effect, is pervasive across many industries and markets, making it an important feature of price dynamics. The asymmetry refers to the phenomenon where prices respond quickly and often completely to cost increases but respond slowly and incompletely to cost decreases. While this asymmetry in cost pass-through has been studied most extensively in the gasoline market (*e.g.*, Borenstein et al. 1997), Peltzman (2000) provides empirical evidence of its presence across a wide range of product markets. Beyond product markets, asymmetric pass-through has also been documented in value-added tax transmission (Benzarti et al., 2020), exchange rates (Pollard and Coughlin, 2004), bank deposit rates (Neumark and Sharpe, 1992), and municipal bonds (Green et al., 2010).

Despite being widely documented, this asymmetry is puzzling because the standard price theory (or comparative statics of price theory) treats cost increases and decreases symmetrically, implying equal price responses in both directions. As a result, research has focused on exploring and identifying conditions under which such asymmetry naturally arises. The most widely accepted explanation emphasizes the role of consumers, citing that inattention or search costs prevent them from obtaining information about cost decreases, thereby weakening competitive pressure to lower prices and leading to slower price adjustments (Yang and Ye, 2008; Tappata, 2009; Lewis, 2011). Other proposed explanations include inventory effects, non-linear price adjustment costs, and tacit collusion, though their relevance may depend on the specific market context.

In this paper, I provide evidence that asymmetric price responses to cost changes occur even in the absence of many conditions previously proposed as potential sources of asymmetry. In doing so, I exploit a unique empirical setting in the wholesale electricity market that allows testing for asymmetry with minimal assumptions and structural constraints. The market I study has a simple structure in which all previously identified sources of asymmetry – especially those involving consumer behavior – cannot explain the documented asymmetry. This finding suggests that asymmetry can naturally emerge from strategic interactions among suppliers, independent of consumer-side factors.

To shed light on the strategic basis of the observed asymmetry, I draw on rich firm-level bidding data available in this market, which reveal firms' strategic decision-making. I find that underlying bidding strategies also exhibit asymmetry, differing systematically between samples with similar fundamentals (e.g., cost and demand conditions) but opposite cost-change directions. This finding points to an inherent asymmetry in strategies that depends on the direction of cost movement, stemming from differences in firms' beliefs about competitors' strategies, which I confirm with a structural estimation of beliefs that rationalize firms' best-response bidding. That is, firms' beliefs become more dispersed following a cost decrease, covering a wider range of strategies, including bid adjustments that do not fully reflect the decreased level of cost. This implies that the greater strategic uncertainty associated with downward cost movements allows strategies in which prices do not fully adjust to the cost decrease to emerge as market outcomes.

The contribution of this paper is to identify a new supply-side mechanism rooted in inherent asymmetries in firms' strategies and beliefs, which can naturally arise from strategic interactions among suppliers. Such a channel is difficult to isolate from consumer-side explanations, but the empirical setting

in this study – where all potential sources posited by the literature can be excluded and where symmetric cost changes generate samples suitable for testing asymmetry – allows for clean identification. The use of high-frequency, firm-level microdata further enables me to uncover how uncertainty embedded in firms' decision-making translates into asymmetric strategic behavior and, ultimately, asymmetric price responses.

Throughout the paper, I leverage a unique cost variation in the electricity market driven by natural gas prices, which provides a proper empirical setting to test for asymmetry. Natural gas prices exhibit upside volatility, creating an environment in which the marginal generation costs of gas-fired power plants rise sharply and then return to pre-increase levels within a short period. This variation creates an ideal setting for examining asymmetric pass-through, as it ensures symmetry in the cost range over which pass-through rates are averaged, with only the direction of cost change differing (Benzarti et al., 2020). Instead of estimating pass-through using the cost variation, I take a slightly different approach by comparing prices between samples before and after a cost increase event – referred to as the pre-increase and post-increase samples – to test whether prices return to their pre-increase levels once marginal costs decrease back to their original level. Since these two samples are not fundamentally different, with market conditions such as marginal costs and demand being similar, prices should return to their initial levels if adjustment to cost change is symmetric. However, I find that prices in the post-increase sample are about 7% higher than in the pre-increase sample, suggesting that output prices do not fully return to their initial levels immediately, indicating asymmetric pass-through.

In addition to providing a clean empirical setting, the wholesale electricity market offers the major advantage of not being subject to the commonly cited sources of asymmetric pass-through. First, because there are no consumers in the conventional sense in this market, consumer-side explanations for asymmetric price responses can be disregarded. Electricity demand in the wholesale market comes from electric utilities and is perfectly inelastic to prices. Thus, there are no end consumers who would learn about cost changes on the supply side and adjust their demand accordingly, ruling out consumer search-cost and inattention channels. Second, the market clears every day and hour, requiring supply-side firms to compete and make swift decisions in response to exogenous market variables such as fuel prices and demand, which vary stochastically over time. This feature ensures that firms' strategic decision-making remains effectively static, leaving them with little incentive to delay adjustments of prices or production. Moreover, because prices are adjusted every hour and all firms are required to participate in these markets, explanations based on differences in price adjustment cost (i.e., menu costs) or adjustment frequency (Gopinath and Itskhoki, 2010) can be ruled out. Lastly, supply-side firms procure natural gas based on daily needs, since it cannot generally be stored, and the spot natural gas prices they observe convey fairly complete information about competitors' costs. This eliminates information asymmetry between firms, particularly regarding costs, as well as inventory effects that could delay price responses (Borenstein et al., 1997).

Therefore, the asymmetric price responses documented in this paper cannot be explained by widely known sources of asymmetry. To investigate the underlying mechanisms, I leverage high-frequency bidding data at the firm and generating-unit levels, which are available because the wholesale electricity market is cleared via a multi-unit uniform auction. Comparing the pre- and post-increase samples, I find that price bids are systematically higher in the post-increase sample, and the stylized peak-hour bidding pattern

– where strategic firms typically bid higher in peak hours than in off-peak hours – disappears, with bids more dispersed around a higher level. These differences vary across firms with different strategic positions, potentially reflecting differences in firms' strategic ability.

Given that observable market fundamentals are similar across samples except for the direction of cost change, the adoption of different bidding strategies in the post-increase sample suggests a change in firm's beliefs about its competitors' strategies. To explore this further, I structurally estimate each firm's beliefs – modeled as ex-ante expected bid distributions of its competitors – that rationalize the observed bidding behavior. In doing so, I do not impose a particular equilibrium assumption, allowing for the possibility that different equilibria or behavioral patterns can arise across these samples, while relying only on the condition that observed bids are best responses. This is feasible due to not having to estimate structural primitives such as marginal costs jointly with beliefs, as the marginal cost of electricity generation can be accurately measured from data. This particularly attractive feature of electricity markets enables the estimation of model primitives without committing to a specific equilibrium concept, and is compatible with both equilibrium and non-equilibrium interpretations of firm behavior (Hortaçsu et al., 2019). Therefore, the beliefs estimated here are not necessarily restricted to equilibrium beliefs but can be interpreted more broadly as subjective beliefs defined over a set of rationalizable strategies of competitors. While the estimation approach remains agnostic about the underlying equilibrium concept, it is consistent with any equilibrium or non-equilibrium model that could have generated the observed market outcomes. In other words, if firms' behavior indeed reflects a particular equilibrium or behavioral framework, the estimated parameters would capture beliefs consistent with underlying mechanisms of those. In fact, since multi-unit uniform auction oligopolies may admit multiple Bayesian Nash Equilibria, the estimated beliefs could correspond to distinct equilibria emerging in the pre- and post-increase samples.

The estimates allow me to assess whether there are systematic differences in beliefs – captured by the mean and variance of ex-ante expected bid distributions – between the pre- and post-increase samples. While the mean of belief distributions is slightly higher in the post-increase sample, the more notable change is an increase in dispersion: the standard deviations are higher than in the pre-increase sample for the majority of firms. This change is more pronounced during peak hours, though a considerable change also occurs in off-peak hours, which explains the more dispersed bidding patterns observed in the bid data.

The key insight behind this finding is that the set of rationalizable strategies differs depending on the direction of cost change. For example, if firms do not increase prices by the full amount of marginal cost increase, they incur per-unit profit loss regardless of competitors' actions; thus, price responses smaller than the cost increase can be rationally excluded from the strategy set. On the other hand, when costs decrease, a firm's decision to decrease prices is driven solely by strategic considerations – only when it believes competitors to lower their prices – because the per-unit profit loss depends on competitors' strategies. Consequently, strategies in which prices are not fully adjusted downward by the size of the cost decrease are not excluded from a firm's rationalizable strategy set and can be a best response to some beliefs, resulting in a much wider strategy set under downward cost movements. I find that when firms face competitors whose strategies they become uncertain about, they tend to raise their bids on average, although the exact pattern and direction of bid adjustment vary across both firm and competitor

types. These findings imply that strategic uncertainty, combined with differences in strategic capabilities, jointly determine the direction and magnitude of their strategic price adjustments.

Although this paper does not explain the observed asymmetry with a specific equilibrium or behavioral model, showing that beliefs and rationalizable strategy sets differ by the cost-change direction is informative, as it indicates that distinct outcomes can emerge across the samples under plausible rational behavior. Thus, the findings of this paper highlight the structural sources of asymmetric price responses without relying on strong equilibrium assumptions.

Literature Review The key contribution of this paper is to identify an additional source of asymmetric price responses beyond those examined in the existing literature. A large body of work has documented asymmetric pass-through and investigated its underlying causes, both theoretically and empirically. The most widely discussed explanations focus on consumer-side mechanisms, such as inattention to supply-side cost changes or higher search costs following a negative cost shock, which suppliers can exploit to delay price reductions (e.g., Yang and Ye 2008; Tappata 2009; Lewis 2011). Wu et al. (2024) show that consumer learning dynamics – the process by which consumers update their biased priors about price distributions – can also generate asymmetric pass-through. On the production-side, researchers have investigated inventory effects (Borenstein et al., 1997), and market power (e.g., Neumark and Sharpe 1992; Borenstein and Shepard 2002) as potential sources of asymmetry. Although not explicitly investigating the underlying source, Benzarti et al. (2020) study asymmetric pass-through of symmetric VAT increases and decreases – an empirical setting closely related to my paper – and provide evidence of persistent asymmetry. Despite the large body of literature, relatively few papers have investigated the role of strategic interaction in explaining asymmetric responses, a gap to which my paper contributes through an examination of strategies and beliefs using detailed micro-level analysis.

While I attribute the observed asymmetry to differences in strategies and beliefs, the analysis does not attempt to identify which specific equilibrium model best characterizes the firms' behavior underlying the observed price responses to cost decreases. Nonetheless, the finding that rationalizable strategy sets and the supporting beliefs differ across samples remains informative, as it implies that distinct outcomes can emerge even without specifying a particular equilibrium. Moreover, because the analysis does not impose belief consistency, the findings are also compatible with non-equilibrium frameworks. In this sense, the paper broadly relates to the literature on firm behavior that departs from standard equilibrium assumptions. For instance, Hortaçsu et al. (2019) introduce bounded rationality through a cognitive hierarchy framework to explain anomalous bidding behavior in wholesale electricity markets, while Doraszelski et al. (2018) adopt a learning model to explain unusual bidding behavior in the early stages of market formation. Although my paper does not estimate a specific non-equilibrium model, it shares the motivation of rationalizing observed behavior that departs from Nash predictions and extends these insights to explain asymmetric pass-through more generally.

More broadly, asymmetric price responses are not confined to a specific market or industry but are closely related to the well-known phenomenon of downward price rigidity – an important feature of price dynamics relevant across many fields of economics. Although not explicitly focusing on asymmetry, a large literature has examined incomplete pass-through in relation to price rigidity. Examples include studies on price adjustment frequency (Gopinath and Itskhoki, 2010), price adjustment costs (Nakamura

and Steinsson, 2008), and markup adjustments (e.g., Goldberg and Hellerstein 2013; Amiti et al. 2019). If these mechanisms operate differently depending on the direction of cost changes, they may generate asymmetric pass-through. My empirical setting, however, is largely free from these sources and, at the same time, provides a more direct test of asymmetry.

Lastly the paper also contributes to the literature on wholesale electricity market competition and strategic interactions within empirical auction frameworks. Prior research has examined strategic bidding behavior in this market (e.g., Wolfram 1998; Hortaçsu and Puller 2008) and used empirical auction models to study various aspects of competition (e.g., Wolak 2007; Reguant 2014; Ryan 2021). More closely related to this paper are studies that combine auction frameworks with analyses of pass-through in electricity markets (e.g., Fabra and Reguant 2014; Kim 2022).

2 Testing the effect of cost change direction on pass-through

2.1 Challenges in testing the asymmetry in price responses

Asymmetric response to cost changes is often referred to as asymmetric cost pass-through. The cost pass-through rate ρ, defined as the response of prices to a *marginal* change in cost, depends on the state at which the marginal change is evaluated. This implies that ρ is heterogeneous and is not generally a constant parameter. For instance, the marginal pass-through rate evaluated at cost level c_0 may differ from that evaluated at c_1 (where $c_0 \neq c_1$). In other words, $\rho(c_0) \neq \rho(c_1)$.

Since the marginal pass-through rate is a point on the $\rho(\cdot)$ function, the rate itself does not vary with the direction of the cost change from the point evaluated, meaning that the marginal rate ρ cannot be asymmetric in principle. Therefore, as demonstrated in Benzarti et al. (2020), testing for price response asymmetry involves using the average pass-through, the average of ρ over a range of cost values. In my context, for a cost change from c_0 to c_1, the average pass-through is represented as:

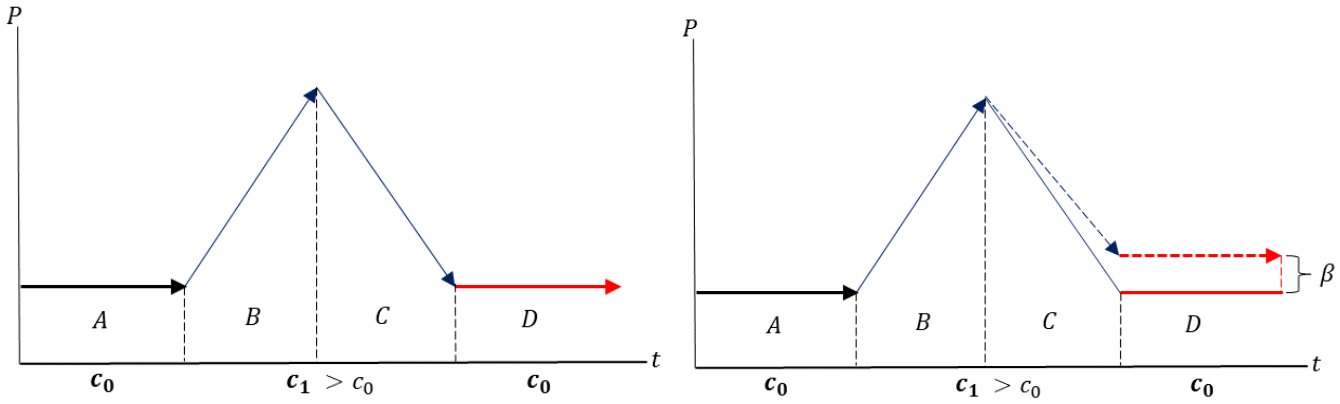
$$\bar{\rho} = \frac{1}{c_1 - c_0} \int_{c_0}^{c_1} \rho(c)\, dc$$

This expression clearly shows that the average pass-through rate varies with the range of costs as well as the start and end points over which the non-constant marginal pass-through ρ is averaged. Different sizes of $\Delta c\,(= c_1 - c_0)$ result in different levels of $\bar{\rho}$, and even with the same Δc, if the range includes different values of c_t, the corresponding ρ values will differ.

Therefore, to properly test for asymmetry, the range of cost changes in both directions should be identical, and the ranges themselves should be symmetric – with cost-increase and cost-decrease ranges given by $[c_0, c_1]$ and $[c_1, c_0]$, respectively. A simple comparison of two average pass-through rates estimated from subsamples that differ in the direction of cost change, but have different composition of cost values or lengths, may not capture the true asymmetry, as these average rates would differ by construction.[1]

To address this problem, one needs an ideal setting in which a cost change in one direction is followed by an equivalent change in cost in the opposite direction. Figure 1 describes such cost change events ideal for testing asymmetry. The figure shows the changes in the output prices when the cost, initially at

[1] Despite this limitation and related concerns, I estimated average pass-through rates for samples differing in the direction of cost changes, as shown in Table A9 in the Appendix.



(a) Symmetric Case (b) Asymmetric Case

Figure 1: Price and Cost Relationship: Symmetric vs. Asymmetric Price Adjustment Cases

c_0, increases to c_1 (block B) and then decreases back to c_0 (block C). Since both the range and the end points of the cost changes are identical in blocks B and C, asymmetry can be tested by comparing the average pass-through rates from each block, i.e., testing whether $\bar{\rho}_B = \bar{\rho}_C$. If the average pass-through rates are the same, as shown in Panel (a), the price response is symmetric. Panel (b) shows the case where the average rates differ, with the price change in block C (dashed line) smaller than in block B ($\bar{\rho}_B > \bar{\rho}_C$), indicating asymmetric pass-through. A similar empirical design was used in Benzarti et al. (2020), which studies asymmetric tax incidence by estimating average pass-through rates for two events in which the tax rate decreased and then returned to its previous level.

However, finding such an empirical setting is generally challenging. Even when one exists, another difficulty is ensuring that other factors affecting equilibrium prices remain constant between these cost-change events (blocks B and C), so that the only difference is the direction of the cost change. For example, if the events are years apart or occur in different markets or regions, there is no assurance that economic conditions are the same between these events, and thus one cannot conclude that differences in the average pass-through rates between blocks B and C provide evidence of asymmetric price response. Moreover, observing multiple such pair of events with equivalent cost ranges in real data is rare, often leaving the analysis with insufficient variation for statistical inference.[2]

2.2 Empirical Approach of this Paper

To overcome the challenges described in Section 2.1, I take a different approach to test asymmetry in price response, leveraging the unique empirical setting and data. Instead of using the cost-change events in blocks B and C of Figure 1, I focus on blocks A and D, denoted as the *Pre-increase* and *Post-increase* samples. Prices in block A are those under a cost of c_0, before the cost increase, while block D shows prices after the cost decreases back to c_0. Although the costs in both blocks are the same, the two samples differ in the direction of the preceding cost movements.

I test whether prices return to the same level as before the cost increase once the cost decreases back to c_0. That is, if other conditions are the same between blocks A and D, symmetric price response to a

[2]Both long lags between events and limited observations posed challenges in Benzarti et al. (2020), where the decrease and subsequent increase in tax rates were five years apart and only one such ideal event was observed.

cost change implies that prices should be identical in both blocks, as in Panel (a) of Figure 1, because the costs are the same. If the price response to a cost change is asymmetric, prices in block D will be higher than that in block A, indicating that prices do not fully return to their previous level despite the cost returning to c_0.

The extent of asymmetry is captured by the difference in price levels between the pre-increase and post-increase samples (blocks A and D), represented by the parameter β in Panel (b). This is analogous to testing whether the average pass-through rate in block B (price change when cost rises from c_0 to c_1) equals that in block C (price change when cost decreases from c_1 to c_0). Specifically, a positive β corresponds to downward price rigidity or the rockets-and-feathers effect.

This empirical approach, which compares outcomes across two distinct samples, can be extended beyond prices to variables such as markups or firm-level bids, enabling further analysis of underlying mechanisms. Moreover, focusing on the pre- and post-increase samples has the advantage of yielding more homogeneous data for the test, since both samples share the similar cost level and market fundamentals, thereby increasing observations and statistical power. By contrast, focusing on cost-change events (blocks B and C) would complicate the analysis, since the magnitude of cost change (i.e., Δc) may vary across events and the cost-change period itself introduces additional market changes that would need to be controlled for. One caveat is that this approach places greater weight on downward cost movements to test the asymmetry, as it does not examine the price response to an upward cost movement (block B).[3]

2.3 Empirical Setting: Natural Gas Price Variation and Electricity Prices

This section explains the empirical setting for applying the approach outlined in the previous section. Specifically, I exploit variation in marginal cost arising from natural gas fluctuations to examine whether wholesale electricity market prices respond asymmetrically to these cost changes.

Wholesale Electricity Market The wholesale electricity market is where electricity-generating firms sell electricity to utilities or retail companies. The market is organized and cleared every hour of the day, thus both prices and generation are determined at an hourly frequency.

The market operates as a multi-unit uniform-price auction. Generators submit supply (energy offer) bids, while demand-side companies submit demand bids. Each bid specifies a price and a quantity, and the market operator aggregates these bids into supply and demand curves. The market is cleared by finding the price at the intersection of these curves, which determines the corresponding generator-level production. The price bid of the marginal unit – the last generator located at the intersection – sets the market clearing price.[4].

The price bid of each generator reflects its marginal cost of electricity generation and a possible strategic markup (i.e., bid markup). Because fuel costs are the main component of marginal cost, changes in fuel prices are directly incorporated into marginal costs. This makes the electricity market a useful empirical

[3]Because the upward cost movement part is not included in the analysis, the test does not indicate whether pass-through of a cost *increase* is complete or incomplete. However, an estimate provided in Table A9 of the Appendix shows that pass-through is close to one in the cost-increasing case.

[4]The uniform-price setting distinguishes this market from a typical product- or firm-level price setting, which is more commonly examined in pricing studies. I discuss how the findings from my analysis can be generalized to the firm-level pricing setting in Section 3.3.5.

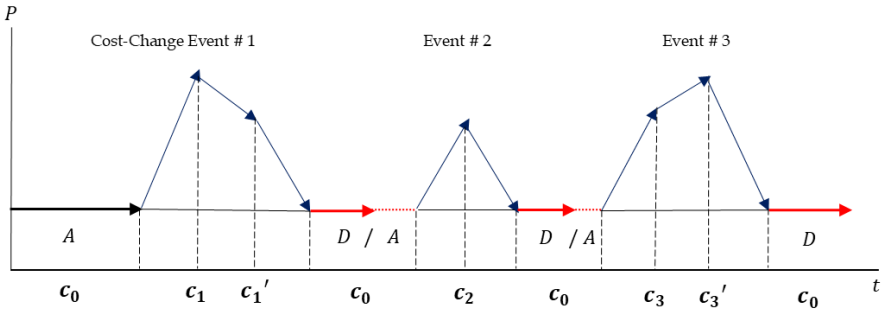


Figure 2: Example of Cost-Change Events in the Sample: Symmetric Case

setting for studying cost pass-through from fuel price fluctuations.[5]

Natural Gas Prices and Cost changes For the analysis, I exploit variation in natural gas prices and study its impact on electricity prices. Since natural gas is an essential input in electricity generation, a change in gas prices implies a cost change, which is ultimately reflected in output electricity prices. The variation in gas prices is mainly driven by weather-related gas pipeline congestion due to increased residential heating demand, making it exogenous to electricity market conditions.[6]

The variation in natural gas prices creates a cost pattern similar to the ideal setting illustrated in Figure 1 for testing the asymmetry of output price responses. A distinctive feature of this variation is that gas prices are volatile on the upside: gas prices rise above the base level and then decrease back to the base level. Marginal costs for gas-fired electricity generation follow the same pattern, creating a unique event in which a cost increase is followed by a decrease within a relatively short time frame.

Specifically, gas prices – and thus marginal costs for gas-fired generators – usually stay around the base level with minimal change across days and hours, similar to block A in Figure 1, where marginal costs are at c_0. As gas prices rise above the base level, marginal costs increase to c_1. After this cost-increasing event, gas prices return to the base level – the same level as before the cost-increase – and the marginal costs return to c_0, as depicted in block D in Figure 1. Thus, marginal costs are the same (or in a similar range) in blocks A and D. Later, in Section 3.2.1, I provide a more detailed discussion and a data-based visualization of gas prices.

While this pattern (shown in Figure 1) is generally preserved in the data, a more realistic pattern resembles that in Figure 2. In the data, I observe multiple cost-change events (e.g., about 20) over time. Observing many such cost-change events increases the size of the sample (blocks A and D), thereby enabling statistical inference on the extent of asymmetry, β, estimated as the difference in prices between blocks A and D.[7] Within each cost-change event, multiple higher-cost days (with $c > c_0$) may occur

[5]Cost pass-through in the wholesale electricity markets has been studied extensively, including Fabra and Reguant (2014) on emissions costs and Kim (2022) on fuel price pass-through.

[6]The congestion driving sharp gas price spikes is primarily due to higher residential heating demand during cold weather, rather than increased demand from the power generation sector. While cold weather may raise electricity use among residential customers, the increase is not large enough to cause congestion. Additionally, daily electricity demand levels on congestion days are not significantly higher than on other winter days. Spot gas prices are determined exogenously in the commodities market, and power generators observe these prices when making production decisions.

[7]This contrasts with Benzarti et al. (2020), where only a single pair of such events (a one-time tax decrease and increase) is observed. For this reason, statistical inference was not possible in Benzarti et al. (2020). To address this limitation, they conducted a separate analysis using VAT changes implemented across EU countries.

before costs return to the original level of c_0, as illustrated in events 1 and 3 in Figure 2. The duration of these cost-change events (the time between the initial increase and the subsequent decrease to the original level) is relatively short, typically lasting several days, with cost changes occurring at the *daily* level. This provides an empirical advantage by ensuring that blocks A and D are not fundamentally different except for the direction of the cost change, which is crucial for identifying how cost-change direction affects price adjustments. Details on how samples A and D are defined are provided in Section 3.2.1.

2.4 Why Other Sources of Asymmetry Do Not Apply in This Market

The wholesale electricity market provides a particularly clean setting in which commonly discussed sources of asymmetry can be ruled out. A large literature explores the causes of asymmetric pass-through (i.e., the rockets-and-feathers effect), with the most common explanation being consumer search costs on the demand side (Yang and Ye, 2008, Tappata, 2009, Lewis, 2011, etc.). The wholesale electricity market, however, does not have an active demand side that responds to prices. That is, the demand side of this market consists of companies such as electric utilities and retail electricity providers, which must acquire electricity regardless of price, making demand almost perfectly inelastic.[8] As there are no end consumers in this market whose consumption decisions depend on information about supply-side cost changes, explanations involving consumer search or demand-side reactions can be excluded. Consequently, any documented price asymmetry in this market cannot be attributed to the demand side.

In this market, price adjustment occurs every hour of the day (with all firms facing the same adjustment frequency) and involves effectively no adjustment costs, as firms are compelled to compete and receive profits based on the cleared prices and quantities in hourly markets. Consequently, differences in price adjustment frequency (Gopinath and Itskhoki, 2010) or price adjustment costs (*i.e.*, menu costs) between cost-increase and cost-decrease situations cannot explain asymmetric pass-through in this market setting. This follows from the market's high-frequency, auction-based design, where market clearing and pricing occur at an hourly frequency, and firms must submit bids and make swift production decisions based on the market conditions of that day and hour.[9]

Because of the nature of market clearing, any explanation involving dynamics (i.e., intertemporal dependencies) also does not apply in this setting.[10] Firms must compete and earn profits in daily markets, making market competition and equilibrium price formation effectively static, with firms' objectives being to maximize same-day profits. Thus, firms have no incentive to take actions today to influence competitors' future strategies.

Moreover, the market variables relevant to firms' pricing and decision-making, such as natural gas prices and electricity market demand, vary stochastically and are exogenously determined. For example, natural gas prices, which form the basis of a firm's marginal cost, are set in a separate, competitive

[8]The electricity sector is divided into wholesale and retail markets, which are largely disconnected. Retail companies (or electric utilities) operate in both, but because they are obligated to meet the electricity demand of residential customers, their goal in this wholesale market is to secure supply regardless of price. For this reason, they do not specify a price when submitting their demand bids.

[9]To be precise, the clearing for all hours within a day occurs together on the day before the actual market, based on projections of hourly market variables and spot gas prices at the time.

[10]There is possibility of dynamic production decisions across hours due to fixed costs, but this generally does not create dynamic dependencies across days. A discussion of the dynamic operation of certain power plants and its impact on the results is provided in the robustness section.

gas market that operates independently of electricity market.[11] These prices fluctuate daily, influenced by many factors, and are therefore not perfectly predictable, even if they may follow certain patterns. Thus, while spot gas prices may appear similar across days, this reflects the typical competitive level of prices rather than prices being fixed over time. Similarly, market demand in the wholesale electricity market is exogenously determined outside of the market, determined by retail consumption, and varies stochastically over time. Retail consumers are unaware of conditions in the wholesale generation sector, and their consumption depends mainly on household activities, external factors such as weather, and retail electricity prices that differ from the wholesale price. Thus, actual demand levels change continuously, varying significantly across both days and hours. Even though intra-day demand patterns often exhibit similar profiles, the realized demand in any given day or hour is not perfectly predictable.

Given the high-frequency nature of market clearing and the exogenous variation in key market variables, the strategic environment faced by firms can be characterized as a repeated static game with a randomly evolving state. In each period, firms play a game given the state, which represents the configuration of the game at that time. The state evolves stochastically but independently of firms' actions, and firms base their production decisions on current-period payoffs rather than on expected discounted payoffs over time.[12] Thus, dynamic pricing incentives are largely absent in this market, which, if present, could slow the adjustment of prices to cost changes (MacKay and Remer, 2022).

Because the strategic environment is not a repeated dynamic game – where the same stage game is played repeatedly with no state transitions – any explanation involving collusion can be ruled out. Collusion, whether explicit or tacit, is more likely to emerge in repeated dynamic settings, as it relies on intertemporal incentives such as punishment strategies that link current strategies to future outcomes. Furthermore, market pricing and bidding behavior in the wholesale electricity market are regularly monitored by multiple agencies, making sustained collusion infeasible. Further discussion of why dynamic considerations do not apply in this setting is provided in Appendix A.4.2.

Lastly, the uniqueness of natural gas as an input also allows me to exclude several potential channels of asymmetry. In settings where inputs can be stored, inventory management creates a lag in the costs and price responses: an input price change today affects costs only after existing inventories are depleted. Such dynamics, combined with asymmetric inventory adjustment costs, have been identified as one explanation for asymmetric pass-through in gasoline prices (Borenstein et al., 1997). In contrast, because natural gas cannot be viably stored, the just-in-time nature of natural gas procurement eliminates inventory effects. Therefore, the spot gas price on the day of production is immediately reflected in the generation cost of gas-fired plants. This also rules out cost-related information asymmetry: the spot gas price observed by firms conveys nearly complete information about competitors' costs, since it is common knowledge that dispersion in individual transaction-level spot gas prices is minimal in a liquid gas market (see Kim (2022) for details).

[11] Spot gas prices change continuously in the market. Even when spot prices rise, the primary driver is not higher electricity consumption, which makes these prices exogenous to the electricity market. Firms could purchase gas through long-term contracts, where forward prices remain fixed throughout the sample period. However, the majority of gas generators procure gas through the spot market.

[12] An exception applies to firms operating a large share of assets with dynamic production, such as those with large fixed costs. However, even for these firms, dynamic production occurs across hours rather than across days.

3 Empirical Analysis

3.1 Data

The main dataset used in the analysis is from the New England wholesale electricity market (ISO-NE). This market allocates electricity through hourly auctions, providing high-frequency data on bids submitted by market participants, as well as corresponding price and production data. The dataset includes supply-side energy offer bids from the day-ahead wholesale electricity market, demand bids, and system clearing prices (i.e., the energy component) for the years 2012 to 2014. The analysis focuses on sample days from October to April (including the winter season) when natural gas price variation is most pronounced.

On the supply side, power-generating firms operate plants using various fuels, including natural gas, coal, oil, hydro, and renewables, with natural gas being the dominant energy source.[13] Data on power plant ownership, fuel types, and capacities are obtained from the ISO-NE Seasonal Claimed Capability data and the EIA-860 form. On the demand side, electric utilities and retail companies submit price-insensitive bids, making demand perfectly inelastic. The analysis therefore considers only aggregate demand, which I measure as the sum of the quantity components of demand bids. To adjust for imports and exports, the hourly net interchange is subtracted from the aggregate demand. Transmission conditions are not incorporated into the analysis.

The natural gas price data used in the analysis are spot natural gas price indices (from *Natural Gas Intelligence*), a commonly used daily measure of natural gas spot prices.[14] Marginal costs are measured using generator heat rates and daily fuel (natural gas) prices. Generating unit-level heat rates (physical efficiencies) are obtained from a separate estimation, described in Appendix A.1.2. The daily gas price index data and the generator heat rates are then combined to construct generator-level marginal costs at the daily level.[15]

3.2 Samples

3.2.1 Pre-Increase and Post-Increase Samples

I divide the sample into three parts – Pre-Increase, Cost-Increase (i.e., cost-change events), and Post-Increase samples – based on the direction and level of gas price changes. The empirical analysis uses only the Pre-increase and Post-increase samples, with cost-increase events used only for dividing these samples. The sample division is exogenous, since natural gas prices vary for reasons independent of electricity market conditions.[16]

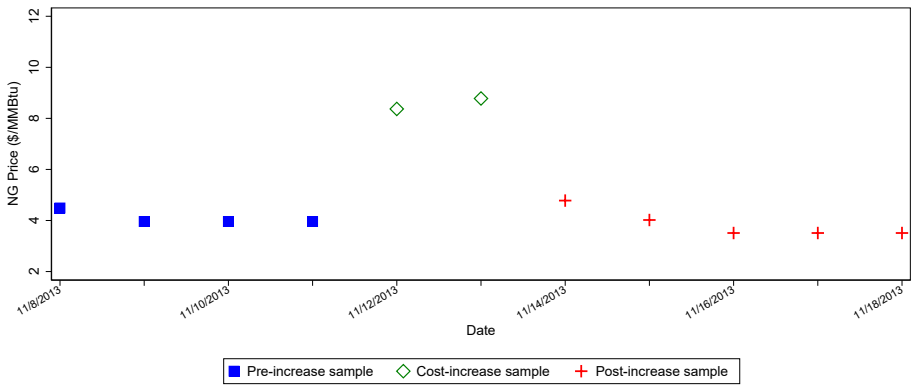
Figure 3 shows a simplified visualization of the sample days divided into three main parts, plotted using daily natural gas spot prices (index) in New England. The first block, the *Pre-Increase* sample

[13]The generation share of natural gas exceeded 50 % during the time period. Note that the generation share of renewables for this time period was very small, less than 5%.

[14]I used Algonquin citygate gas price index data. Index data for other fossil fuels, such as petroleum products and coal, are also used, although these fuels are not the primary focus of the analysis.

[15]Because heat rate represents physical efficiency, it is fixed throughout the sample. A single heat rate parameter is estimated for each gas-fired generating unit. The sample used for heat rate estimation does not overlap with the samples utilized in this paper. More details of the estimation can be found in Appendix A.1.2.

[16]See Section 2.3 for details



Notes: The figure presents a subset of the dataset, selected to visualize how days are classified into each sample group. Daily natural gas prices are shown together with sample classifications: squares: pre-increase sample; crosses: post-increase sample; diamonds: cost-increase sample.

Figure 3: Visualization of Sample from Data

(corresponding to block A of Figure 1), includes consecutive days with base-level gas prices around \$4/MMBtu, before any significant cost increase occurs. The second block, the *Cost-Increase* sample (or set of cost-increase events), follows the pre-increase sample and includes days when gas prices rise above the base level.[17] The third block, the *Post-Increase* sample (corresponding to block D of Figure 1), consists of days when gas prices return to the base level following a cost increase event and before the next one. Because the data include multiple cost-increase events, there are several post-increase blocks, which are pooled into the post-increase sample. Panel (a) of Figure A1 in the Appendix shows the visualization of the main sample division for the extended sample.

In an alternative categorization, I reclassified some days immediately preceding a subsequent cost-increase event – originally part of the post-increase sample – into the pre-increase sample.[18] The results were qualitatively similar to the main categorization, and the alternative categorization produced stronger results in some cases, as will be discussed in Section 3.3.3. Panel (b) of Figure A1 in the Appendix shows the visualization of the alternative sample division.

The pre-increase and post-increase samples are balanced in terms of market variables. Table 1 presents summary statistics for the gas prices, marginal cost of gas-fired (marginal) units, and demand, separately for pre- and post-increase samples. The two samples are well balanced, exhibiting nearly identical distributions across key variables.

3.2.2 Peak and Off-Peak Hours

Since the market clears every hour (h) of the day (t), each market in the sample is indexed by (t, h). I further divide hours into peak and off-peak samples, in addition to dividing days based on gas price levels and the direction of cost change.

Competition and pricing strategies in the wholesale market vary across hours. During early hours, when electricity demand is low – referred to as *off-peak* hours – competition is typically more intense

[17] The duration of these events varies – from a single day to several consecutive days – as do price levels within them. Gas price levels depend on the severity of pipeline congestion.

[18] This alternative division presents challenges, such as short length of post-increase blocks and the difficulty of selecting the number of reclassified days.

Sample	Stats	NG price ($/MMBtu)	MC ($/MWh)	Demand (MW)
Pre-Increase	Mean	4.30	37.5	13,230
	Med	4.27	37.7	13,317
	Min	3.90	24.1	6,197
	Max	5.18	70.0	23,049
	SD	0.27	6.9	3,430
	N	1,340	1,324	1,340
Post-Increase	Mean	4.55	39.3	13,356
	Med	4.64	40.1	13,175
	Min	3.51	22.1	6,092
	Max	5.16	73.8	23,081
	SD	0.37	7.2	3,181
	N	1,517	1,509	1,517

Notes: NG price is the daily spot gas price index, MC is the marginal cost of a non-dual marginal units, and demand is the hourly aggregate demand. The sample includes day-hour pairs where non-dual natural gas generating units set the market price.

Table 1: Summary Statistics: Pre-Increase and Post-Increase Samples

because low demand coincides with sufficient idle capacity. As a result, off-peak hours are characterized by low market power, leaving firms with limited scope for strategic behavior. On the other hand, in *peak* hours, demand is high and idle capacity is scarce, allowing firms – especially those with scale – to strategically utilize their generation assets and exercise market power.

I exploit these differences in market outcomes and strategic behavior between off-peak and peak hours in my analyses of prices and strategies. I categorize hours from 12 AM to 7 AM as off-peak and hours from 8 AM to 11 PM as peak.[19]

3.3 Main Analysis

3.3.1 Price difference between pre- and post-increase samples

The first set of analyses examines whether there is a statistically significant difference in market prices of electricity between the *pre-increase* and *post-increase* samples. The main specification is shown below in equation (1):

$$P_{th} = \alpha + \beta \text{ Post-Increase}_t \ + \gamma X_{th} + \eta + \varepsilon_{th} \tag{1}$$

P_{th} is the hourly wholesale electricity price that clears the entire system (i.e., the energy component price).[20] The main variable of interest is the indicator Post-Increase$_t$, which distinguishes the pre- and post-increase samples. The control variables X_{th} include market fundamentals that affect prices, such as hourly aggregate demand (Demand$_{th}$) and the marginal cost of the *marginal* unit clearing the market (mc^*_{th}).[21] Year and hour fixed effects are specified in η. Standard errors are computed using Newey-

[19] As a robustness check, I also use an alternative categorization that splits peak hours into 8 AM - 3 PM and 4 PM - 11 PM, treating the latter as more peak. The results are qualitatively similar.

[20] This price does not reflect local transmission conditions. I abstract from transmission congestion throughout the analysis.

[21] The market price is set by the price bid of the last generating unit at the intersection of the system's supply and demand curves, denoted as the *marginal* unit. Therefore, I include only the marginal cost of this unit in the regression, as it is relevant for the market-clearing price. Nevertheless, the full distribution of marginal costs is also important, as it

	(1)	(2)	(3)	(4)	(5)
		Full Sample		Off-peak	Peak
	P_{th}	log (P_{th})	P_{th}	P_{th}	P_{th}
Post-Increase$_{t,h}$	3.170***	0.072***	2.599***	2.739***	3.697***
	(0.480)	(0.011)	(0.452)	(0.373)	(0.542)
$Peak$			−0.918		
			(0.674)		
Post-Increase$_{t,h} \times Peak$			0.940**		
			(0.395)		
Hour FE	✓	✓	x	✓	✓
Year FE	✓	✓	✓	✓	✓
N	2,833	2,833	2,833	1,114	1,719

Notes: Standard errors in parentheses. * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$. Newey-west standard errors are computed. The sample consists of markets where non-dual natural gas-fueled generating units are marginal.

Table 2: Main Price Analysis Results

West estimator with an appropriate lag to account for potential autocorrelation and heteroskedasticity in hourly market prices.

The empirical design aligns with the framework in Figure 1. Therefore, a statistically significant and sizable β, after controlling for market fundamentals, would indicate a systematic price difference attributable to the direction of the cost change, which is the only factor distinguishing the samples.

Table 2, column (1), presents the full-sample estimation result: on average, prices in the post-increase sample are approximately \$3.17/MWh higher than in the pre-increase sample, representing a 7.2% difference, as shown in the logged-values regression in column (2). I also examine how the β estimate differs between peak and off-peak hours, as shown in columns (3)-(5) of Table 2. The price differences are evident in both off-peak and peak hours, with larger differences during peak hours. This is particularly clear in the subsample regressions shown in columns (4) and (5), where the regression is run separately for off-peak and peak hours. These results suggest that the factor driving asymmetric price responses is present in both periods, but slightly more pronounced during peak hours, when strategic decision-making plays a greater role in price determination.

3.3.2 Markup difference

Since the equilibrium price is composed of cost and markup, the fact that prices do not return to pre-increase levels implies that markups are not restored to the pre-increase levels. While the main analysis indirectly captures the markup component by examining price differences conditional on marginal costs, I explicitly test how the markups of price-setting marginal units differ across samples by running a variant of equation (2) with markup, $P_{th} - mc^*_{th}$, as the dependent variable. The markup here is the *market-level* markup, defined as the bid markup ($b^*_t - mc^*_{th}$) of the marginal firm-unit that sets the market price in day t, hour h.

Table 3, column (1), shows that markups at the margin are on average higher in the post-increase

determines the shape of the supply curve. The changes in this distribution are examined later when analyzing firms' bid distributions.

	(1) Full sample	(2) Off-Peak	(3) Peak
		Markup_{th}	
Post-Increase_t	1.373^{**}	0.934^{**}	1.924^{***}
	(0.479)	(0.376)	(0.627)
Demand_{th}	0.0015^{***}	0.0006^{***}	0.0018^{***}
	(0.0001)	(0.0001)	(0.0001)
Hour FE	✓	✓	✓
Year FE	✓	✓	✓
N	2,833	1,114	1,719

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are computed using newey-west method. Using only when the non-dual natural gas units are marginal. The unit of demand is MWh.

Table 3: Marginal Markup Analysis Result

sample than in the pre-increase sample. When further dividing the sample into off-peak and peak hours, as shown in columns (2) and (3), the markups increased more in peak than in off-peak hours, though the extent of increase in off-peak hours is also noticeable.

There are several takeaways from the markup analysis. In a static, competitive environment, there is no clear reason why markups are systematically higher in the post-increase sample and do not return to previous levels, conditioned on all other market variables influencing firms' markup being the same. A well-known explanation in the literature attributes asymmetric markups to consumer inattention and weak demand response, where firms exploit delayed or muted consumer reactions to sustain higher markups in cost-decreasing situations. However, as demonstrated in Section 2.4, consumers and information frictions are absent in our empirical setting. Therefore, this finding suggests another factor is at play causing these differences.

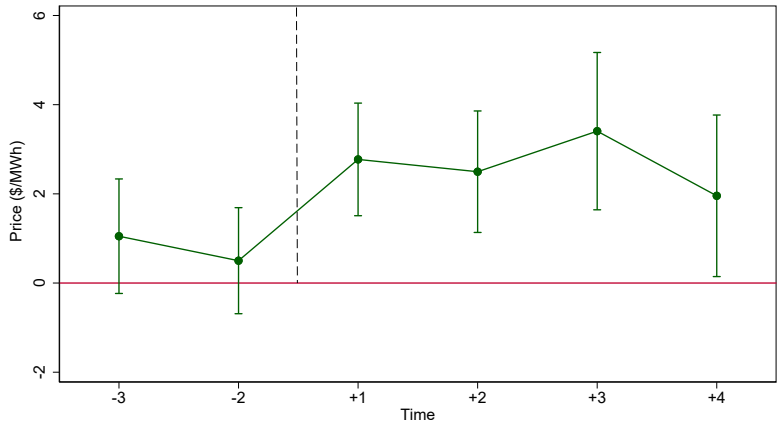
The finding that the average markup difference between the pre- and post-increase samples is smaller than the price difference shown in Table 2 suggests that the shift in the firm-level markup distribution is not uniform. If all previously marginal firms in the pre-increase sample had uniformly raised their markups in the post-increase sample, the overall bid distribution and the composition of marginal units would have remained unchanged, and the markup difference would have been similar to the price difference. Therefore, the smaller markup difference reflects a non-uniform shift in the firm-level bid markup distribution, as well as changes in the identity and composition of firms near the margin.[22]

The *market-level* markups used in this analysis do not capture the overall picture of competition, as they reflect only the ex-post marginal firm's markup, which depends on both exogenous market variables and the bid distribution of all potentially marginal firms. Therefore, I examine bidding strategies across all firms with a micro-level analysis of firm-specific pricing behavior, which follows in Section 4.

3.3.3 Price dynamics within the post-increase sample

Asymmetry in the speed of price adjustment or in the size difference? The estimate β captures the *average* price difference between two samples that differ in the direction of cost changes, controlling for

[22]For instance, Figure B1 in the Online Appendix shows that the composition of marginal units changed considerably between the pre- and post-increase samples.



Notes: The graph shows the estimated price difference ($\hat{\beta}_{1,k}$) for each period (*Time*) $k = \{-3, -2, +1, +2, +3, +4\}$, relative to the baseline comparison period $k = -1$. Time $k < 0$ is part of the pre-increase sample, and $k > 0$ is part of the post-increase sample. Confidence intervals are constructed using Newey-West standard errors (at the 5% significance level).

Figure 4: Price Dynamics: price change $\pm k$ days since the cost-increase event

relevant market conditions. A natural question, however, is whether prices in the post-increase sample gradually converge toward pre-increase levels, which relates to the broader literature on the *speed* of convergence. Studies on asymmetric pass-through, particularly in gas station pricing, suggest that price asymmetries gradually disappear (Borenstein et al., 1997; Lewis and Noel, 2011). In this literature, asymmetry refers to prices declining more slowly than they rise – that is, a difference in adjustment speed. Other studies, however, quantify asymmetry in terms of level differences in prices or pass-through estimates (Peltzman, 2000; Benzarti et al., 2020). Thus, it is important to distinguish whether the asymmetry found in my analysis pertains to adjustment speed or the magnitude of price differences.

I argue that quantifying price asymmetry in my empirical setting captures asymmetry in both magnitude and adjustment speed. Specifically, the observed price difference between the pre- and post-increase samples can be interpreted as reflecting differences in adjustment speed, because market clearing (and price adjustment) occurs hourly and gas prices that determine firms' marginal costs are updated daily. In this context, if prices following a cost decrease do not return to pre-increase levels despite firms optimizing on the day of the cost decrease, it indicates a delayed response, or asymmetry in the speed of adjustment. Note that in industries where firms choose when to adjust prices, the physical time between adjustments, rather than the adjusted price level, serves as an indicator of the speed of adjustment. By comparison, in my setting, where frequent adjustments are mandated by market design, observing higher prices after a cost decrease suggests a lagged response similar to that in markets with infrequent price changes.

Thus, the concept of adjustment speed is shaped not only by the physical time frame but also by how pricing behavior aligns with market dynamics. Nonetheless, I present additional analyses of price adjustments over time in the following subsection, which are not part of the main specification.

Do prices in the post-increase sample decrease over time? I employ an event-study analysis (without controls) to examine price convergence over time, using cost increases as events. I estimate the

following specification:

$$P_{th} = \Big(\sum_{k \in \{-3,\ldots,+4\}} \beta_k D_{t-k} \Big) + \gamma X_{th} + \eta + \varepsilon_{th} \tag{2}$$

The coefficients β_k capture price patterns relative to the baseline $k = -1$ (the day before the event, part of the pre-increase sample). Coefficients for $k < 0$ reflect pre-increase prices, while those for $k > 0$ reflect post-increase prices.[23]

Figure 4 plots the estimated β_k, showing that post-increase prices are higher than the baseline for several days, declining slightly over time though not strictly monotonic (β_k for $k > 0$), while pre-increase prices are statistically indistinguishable from the baseline (β_k for $k < -1$). Overall, these results indicate that a systematic price difference between the pre- and post-increase samples persists for several days, with evidence of a gradual, albeit nuanced, decline. Although not the primary focus, this event study also helps identify the duration of post-increase pricing patterns, which informs the alternative post-increase sample categorization described in Section 3.2.1.

3.3.4 Incorporating cost-increase period information

The cost-increase (shock) sample serves only as an exogenous event for dividing the data and has not been used in the analysis so far. However, although competition in this market is static, firms' strategies and beliefs may still be influenced by the characteristics of the cost-increase periods. For example, firms' expected strategies in the post-increase sample could differ depending on whether the cost increase was larger or more abrupt. To assess this, I incorporate the magnitude and timing of cost declines into the price analysis using Equation (2). I find that post-increase prices are higher when costs decline from a higher level and when the return to the base level is immediate rather than gradual. Details of the analysis and results are provided in Appendix A.2.4.

3.3.5 General applicability of results: comparing single market price and firm-level pricing

The pricing mechanism in this market differs from a typical setting in which firms set their own product prices. Instead, the market clears through a uniform-price auction, resulting in a single market price for all firms. Consequently, the price analysis in this paper does not involve firm-level prices. Given this unique mechanism, it is important to examine how the absence of firm-specific pricing affects the analysis and how adopting a single market price aligns with standard practices in pricing research to ensure broader applicability.

A key distinction between uniform and firm-level pricing is that, while firms in firm-level pricing cases receive the prices they set, firms in a uniform price auction receive the market-clearing price, which may differ from their price bids. However, the price bids of interest in this analysis are those from firms expecting their bids would set the price which they eventually receive (i.e., ex-ante marginal bids). Thus, the market setting is not fundamentally different from one where firms set prices to maximize their ex-ante expected profit, making the uniform-price mechanism comparable to firm-level pricing strategies.

Furthermore, using a single market price in the analysis is comparable to using representative price indices, a common approach in price analysis studies. The uniform price in an auction-based market,

[23] The cost-increase event itself ($k = 0$) is excluded from the analysis.

despite being a single value, indirectly reflects individual firm-product prices, much like a price index, as both are shaped by the distribution of individual-level prices. Moreover, markets often feature numerous firms, variety of products, and a wide range of prices, making firm-level price data impractical for analysis. Consequently, even in markets with firm-level pricing, most empirical studies of price movements or pass-through effects rely heavily on aggregate or average price measures. In particular, pass-through analyses involving cost variations over time frequently use aggregated prices or sales-weighted average price indices to capture meaningful price variations. This approach is also prevalent in macroeconomics and trade economics research on price adjustments.[24]

3.3.6 Robustness checks

The crucial condition underlying the analysis is that the pre- and post-increase samples share similar market environment, aside from the direction of the cost change. I conduct several robustness checks to ensure this, investigating whether any systematic differences in operating conditions carry over from the cost-increase period. Additional robustness checks are available in Appendix A.2.

The first check re-estimates the price regression using a sample that excludes the first day of the post-increase period, addressing the possibility that generators may not immediately return to their usual operating and bidding behavior on the first day of the post-increase sample. Because the analysis relies on day-ahead market data – where bids are submitted roughly a day before actual generation – one might worry that bids and prices do not fully reflect the gas price decrease in time. While this concern is mitigated by the fact that gas trading also occurs on a day-ahead schedule, I nonetheless test robustness by excluding the first day of each post-increase block. Columns (1) and (2) of Table 4 show that the estimates remain consistent with the main results (shown in Table 2), indicating that the findings are not driven by a lagged generator response.

The second robustness check addresses small differences in gas prices between the pre- and post-increase samples; gas prices are not identical. Although the main regression already controls for the marginal cost of the marginal unit, I further restrict both samples to days and hours that closely match on gas price and other conditions (e.g., demand, daytime).[25] Columns (3) and (4) of Table 4 show the results. Although the sample size is smaller, the estimates are statistically significant and even larger in magnitude, despite the restricted samples having virtually identical average gas prices, as shown in Table A8 in Appendix.[26]

In the next robustness check, I repeat the main analysis using an alternative post-increase sample categorization described in Section 3.2.1. Here, the first n days of the post-increase block (of length K) are kept in the alternative post-increase sample, with the remaining days $(K-n)$ of the block reassigned to the pre-increase sample of the subsequent cost-increase event. The choice of n is guided by the price dynamics analysis in Section 3.3.3, with a default of $n = 4$. An example of this sample division is shown in Figure A1 of the Appendix. Columns (5) and (6) of Table 4 show that the results remain statistically

[24] See Goldberg and Hellerstein (2013) for a review.

[25] Specifically, for each post-increase day, I identify the most similar pre-increase day in terms of gas price, demand, daytime, and other factors. I repeat the process symmetrically for each pre-increase day.

[26] The average gas prices are \$4.45/MMBtu for the pre-increase, and \$4.43/MMBtu for the post-increase sample. I also estimated a version where both the first and second robustness checks are combined; using the matched sample and with the first day of the post-increase sample dropped. I find estimates higher than in the main results: β =3.35 for the price regression and 0.079 for the logged price regression.

	a. First-day Dropped		b. Sample Matched		c. Alternative cat		d. Generator q_{ijt}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	P_{th}	log (P_{th})	P_{th}	log (P_{th})	P_{th}	log (P_{th})	Dual	Gas
Post-Increase$_{t,h}$	3.081***	0.069***	3.627***	0.086***	3.222***	0.0754***	−0.319	−7.371*
	(0.491)	(0.012)	(0.680)	(0.017)	(0.436)	(0.011)	(1.529)	(4.284)
Hour FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	2,543	2,543	481	481	2,106	2,106	45,516	62,208

Notes: Standard errors in parentheses. * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$. Standard errors computed using Newey-west method for columns (1)-(6), and clustered at generator level for (7)-(8) regressions. Price regressions in columns (1)-(6) use market outcomes when the non-dual natural gas units are marginal. Columns (7)-(8) presents plant-level generation (MWh) regressed on the post-increase indicator.

Table 4: Robustness Checks

significant, with magnitudes larger than in the main regression. Further details of this alternative division and analysis are provided in Appendix A.2.

I also examine whether generation at the power plant level is comparable between the pre- and post-increase samples, addressing broadly two concerns related to the preceding high gas price period. First, since the surge in gas prices is caused by the pipeline congestion, one concern may be that gas shortages persisted and affected generation of gas-fired plants in the post-increase sample. However, the gas supply cuts were not a major issue during the shock, as congestion reflected the scarcity value of pipeline capacity rather than an actual block in gas deliveries. A second concern is that some dual-fuel plants may have switched from gas to oil during the high gas price period and continued to do so even after gas prices returned to the base level.[27] If so, generation and bidding patterns would differ between the pre- and post-increase samples. To address these concerns, I check whether the operation patterns of gas-fired and dual-fuel plants differ significantly between the pre- and post-increase samples. I regress hourly plant-level day-ahead generation on the post-increase indicator, reported in columns (7) and (8) of Table 4. Column (7) shows no significant change in dual-fuel plant's generation, suggesting that fuel switching behavior did not persist after gas prices decreased. Column (8) shows that generation from non-dual gas plants changes only slightly and is not strongly statistically significant.[28]

4 Investigating the difference in the bidding strategy

In this market, because pricing is determined through a multi-unit uniform auction, firms influence the market price only indirectly by strategically adjusting their bids ex ante.[29] Therefore, to further investigate the price differences documented in the previous section, I examine whether there are any

[27]Fuel switching among dual-fuel gas units in New England wholesale market was prevalent during the cost-increase sample. However, operations of plants using other fuels, such as coal or nuclear, are not directly affected by gas price variation. See Kim (2022) for details.

[28]Histogram plots of unit-level generation, shown in Figure B3 of the Online Appendix, further confirm that generation patterns are not systematically different across samples.

[29]This differs from many other markets in which each firm would set and receive a price for its own product, as explained in Section 3.3.5. Nevertheless, competition in this setting is similar to price competition, as firms choose price bids that maximize their profits from an ex ante perspective, anticipating that they will receive that price in the equilibrium. It could also be viewed as quantity competition, as a firm can adjust its price bid to adjust the quantity it supplies in equilibrium.

differences in strategic bidding behavior between the two samples. A key advantage of the dataset is that I observe the optimal bidding decisions of all firms at an hourly frequency, which allows me to investigate the changes in bidding strategies at both the firm and generating unit levels. This micro-level analysis further links the documented changes in bidding strategies to the documented price differences between the samples.

4.1 Description of Bidding

In the market indexed by (t, h), firm i $(i = 1, \ldots, N)$ submits a bid schedule, $< b_{ijkth}, q_{ijkth} >$, which includes the price bid b_{ijkth} and the quantity bid q_{ijkth} for each of its unit j $(j \in \mathcal{J})$. Each unit's bid can have multiple steps, denoted by k. The bid reflects the willingness to supply q_{ijkth} at a price greater than or equal to b_{ijkth}. In this auction, quantity bids are typically fixed, and firms primarily adjust the price bid b_{ijkth} to respond strategically. [30] Firms submit bids that maximize their expected profits while considering their expectations about the bids of competitors. A formal representation of optimal bidding model will be detailed in Section 6.

Although I observe all bids submitted by participating firms and their generating units, only the bids with a positive probability of setting the market price (*i.e.*, ex-ante marginal bids) are considered strategically relevant in a multi-unit uniform auction. Therefore, I examine the bids of potentially marginal units – those with price bids within a close range around the ex-post equilibrium price (e.g., the ± \$5/MWh), most of which are natural gas-fired generators.[31] Firms may use multiple marginal units for strategic bidding, with larger firms typically employing more units. I allow for this in the analysis but, for each generating unit, retain only the step bid (k) closest to the ex-post equilibrium price.

4.2 Bid markup Analysis

4.2.1 Bidding Difference between pre- and post-increase samples

An initial examination of the bidding data suggests a change in bidding patterns, shown in Figure A2 of the Appendix, where I compare the distribution of price bids, b_{ijkth}, between the pre- and post-increase samples. That is, the relative ranking of units' bids across quartiles is not preserved, indicating that firms adjusted their bidding strategies in the post-increase sample. See Appendix A.3.1 for details.

The figure is only suggestive in that the factors that could result in differences in bids are not controlled for. Thus, I bring this to a regression setting, with the bid markup $(b_{ijth} - mc_{ijt})$ of potentially marginal units as main dependent variable. The bid markup, a strategic component of a bid, is the difference between the price bid of the unit and its marginal cost.[32] I run the following regression shown in

[30] Since firms can own multiple units, their submitted bids are often referred to as supply schedules, $S_{ith}(p_{th}, q_i)$. This notation follows Wilson (1979) and Hortaçsu and Puller (2008), though I use a slightly different notation throughout this paper.

[31] I tried two similar approaches to select the marginal units. First, I selected units with price bids within a close range around the ex-post equilibrium price (e.g., the ± \$5/MWh). Second, I compute the probability of being marginal for each firm (i) and generating unit (j), $\frac{\partial p_{th}}{\partial b_{ijkth}}$, by constructing each firm-generator's residual demand curve using ex-post observed bids. Since both approaches yield a similar set of marginal units, I opt for the simpler method in the main analysis. While both approaches have limitations – neither fully captures the ex-ante probability based on each firm-unit's residual demand distribution – they help identify most close-to-marginal units.

[32] A formal expression of bid markup is presented in Equation (7) in Section 6.

	(1)	(2)
	$b_{ijth} - mc_{ijt}$	
Post-Increase$_t$	1.024^{**}	0.552^{*}
	(0.350)	(0.321)
Peak$_h$		-0.110
		(0.372)
Post-Increase$_t \times$ Peak$_h$		0.784^{**}
		(0.340)
Hour FE	✓	x
Year FE	✓	✓
Firm FE	✓	✓
N	55,214	55,214

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors clustered at the day (t) and firm (i) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (*i.e.*, marginal) are used for estimation. Demand variable is demeaned (unit: MWh).

Table 5: Bid markup regression: Full sample

equation (3), the specification of which is similar to that in equation (1):

$$b_{ijth} - mc_{ijt} = \alpha + \beta \text{ Post-increase}_t \ + \gamma \text{ Demand}_{th} + \eta + \varepsilon_{ijth} \tag{3}$$

The analysis includes bid markups of gas-fired generators, the marginal cost of which are directly affected by gas price changes. To ensure consistency with the price regression, I use only day-hour markets (t, h) in which a (non-dual) gas-fired unit sets the equilibrium price.

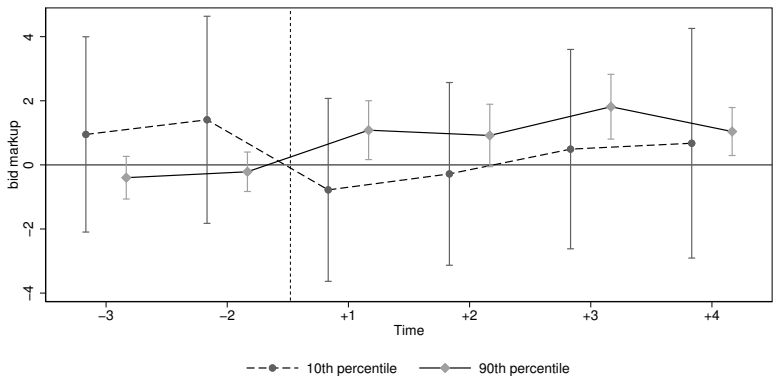
Table 5, column (1), shows a positive and significant coefficient for the post-increase sample (Post-Increase$_t$), indicating systematic overbidding (higher bid markups) relative to the pre-increase sample. Column (2), which divides the sample into peak and off-peak hours, shows that the increase is more pronounced in the peak-hour sample, as reflected in the interaction term. This regression, however, only captures the average difference in the first-order moments of bid markups across samples.

Additionally, I estimate a regression of bid markup quantiles on event-time dummies, using a specification similar to that in Equation (2) and setting the coefficient at $t = -1$ as a baseline. This allows me to trace the dynamics of bid markups around the cost-increase event. Figure 5 shows that, after the cost-increase event, bid markups diverge across firms and units: high-quantile markups are significantly higher than the pre-increase baseline, whereas low-quantile markups do not differ significantly, implying greater dispersion in bidding strategies. Figure A4 in the Appendix presents the estimates for off-peak and peak-hour samples, showing that bid dispersion in more pronounced during peak hours.

4.2.2 Bidding Differences by firm group

To examine differences in bidding patterns across firms, I compare pre- and post-increase bid markups by firm size and generation mix.

Firm grouping by size First, I categorize firms into four groups based on their total generation capacity and the number of generating units. Firms that operate a single small-scale generating unit



Notes: The graph shows the estimated bid markup difference ($\hat{\beta}_{1,k}$) for 10th and 90th percentiles for each period (*Time*) $k = \{-3, -2, +1, +2, +3, +4\}$, relative to the baseline comparison period $k = -1$. Time $k < 0$ is part of the pre-increase sample, and $k > 0$ is part of the post-increase sample. Confidence intervals are computed using standard errors clustered at generating unit level (5% significance level).

Figure 5: Bid markup dynamics: ± k days since the cost-increase event (10^{th} and 90^{th} percentiles)

(with capacity below 100 MW) are categorized as *Fringe* firms, which are known for being nonstrategic bidders in the market.[33] *Small* firms include those with reported total capacity between 100 MW and 500 MW, *Medium* firms have capacities between 500 MW and 1,000 MW, and *Large* firms have total capacity exceeding 1,000 MW (up to 4,000 MW). All non-fringe firms operate multiple generating units and submit multi-step bids.

Firm grouping based on generation mix While firm size is the most frequently used indicator of firm strategy and market power, firm characteristics other than size may also affect strategic decisions. Therefore, I categorize firms based on their generation mix, using only those with substantial scale and multiple generating units.[34]

Heavy base firms operate nuclear baseload generators and some gas-fired marginal generators that can be utilized strategically, though the capacity share of these strategic units is smaller than that of other firm types. The *Gas Large* firms operate only natural gas-fired generators, which are marginal generators almost every hour. Gas large firms actively engage in strategic bidding by submitting multi-step bids (typically five to ten steps), as nearly all of their units are potentially marginal. The *Gas/Oil Mix* firms operate a mix of gas- and oil-fired generators, primarily using gas-fired units and employing the higher-cost oil generators only during peak hours. The *Other Mix* firms have a diverse portfolio combining base generation (e.g., biomass, waste, or coal) with marginal generation (e.g., gas or oil). The key distinction between Gas/Oil Mix and Other Mix firms is that the former lack base generation, whereas the latter own a considerable share of it. Similarly, while both Heavy Base and Other Mix firms operate baseload units, Other Mix firms have a larger proportion of marginal gas-fired generators. Finally, *Peakers* operate only during peak hours, relying on scarcity rents to recover their high fixed start-up and ramping costs.

[33]Fringe suppliers typically submit single-step constant bids that are invariant across days and hours. For these firms, I use bids b_{ijth} instead of bid markups in the analysis due to the small sample size and lack up bid markup variation, which makes estimating heat rates (marginal costs) difficult.

[34]The importance of generation mix to better understand firms' strategic interactions in the wholesale market has been emphasized in Kim (2025) and Fabra and Llobet (2025).

	(1)	(2)	(3)	(4)
	< 100	[100, 500)	[500, 1000)	> 1000
	fringe	small	med	large
	$b_{ij,th}$		$b_{ij,th} - mc_{ij,th}$	
(A) Full Hours				
Post-Increase$_t$	0.240	1.080^{***}	0.917^{**}	1.034^{***}
	(0.741)	(0.378)	(0.399)	(0.333)
(B) Off-Peak Hours				
Post-Increase$_t$	-0.106	0.554	0.172	0.488^{*}
	(0.595)	(0.331)	(0.315)	(0.261)
(C) Peak Hours				
Post-Increase$_t$	0.999	1.254^{**}	1.736^{***}	1.484^{***}
	(1.436)	(0.459)	(0.573)	(0.452)
Hour FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
N (full)	333	10,632	14,132	29,468
N(offpeak)	200	2,549	6,288	12,542
N(peak)	133	8,083	7,844	16,926

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at day (t) and firm (i) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable (demeaned within each firm group, unit MWh) is also specified but not reported in this table.

Table 6: Bid markup regression: firm group by size

Results I run separate regressions of equation (3) for each firm group, using the full-hour sample (row A), off-peak hours (row B), and peak hours (row C). Table 6 reports results by firm size. As shown in row A, overall bid markups are higher in the post-increase sample for all firm groups – except fringe firms – as reflected in the positive and significant estimates of the Post-Increase$_t$ variable. Although this result appears to be mainly driven by higher bid markups in peak hours (row B), where all firm types except fringe firms show increases, large firms have higher post-increase bid markups in off-peak hours as well (row C). Importantly, bid markups in the post-increase sample are not necessarily larger for bigger firms, highlighting the need for generation-mix-based groupings; for example, the higher bid markups of small-scale firms are largely driven by the peaker firms in this category.

Table 7 shows results by generation mix-based firm groups. Although overall bid markups are higher in the post-increase sample for all groups except Heavy Base firms (row A), the off-peak and peak regressions reveal more heterogeneous patterns. That is, Gas Large and Gas/Oil Mix firms apply higher bid markups in both off-peak and peak hours, with the extent being larger in peak hours, whereas Heavy Base and Other Mix firms have higher post-increase bid markups mainly in peak hours, and to a lesser extent than other groups. Peaker firms, which operate primarily during peak hours, also show higher bid markups post-increase.

	(1)	(2)	(3)	(4)	(5)
	Heavy Base	Gas Large	Gas/Oil mix	Other Mix	Peaker
			$b_{ij,th} - mc_{ij,th}$		
(A) Full Hours					
Post-Increase$_t$	0.416	0.952***	1.314***	1.008**	2.914**
	(0.470)	(0.315)	(0.429)	(0.429)	(1.076)
(B) Off-Peak Hours					
Post-Increase$_t$	−0.079	0.601**	0.775*	−0.374	–
	(0.354)	(0.231)	(0.374)	(0.625)	–
(C) Peak Hours					
Post-Increase$_t$	1.950*	1.611***	1.478**	1.341**	3.521**
	(0.920)	(0.508)	(0.515)	(0.491)	(1.266)
Hour FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
N (full)	4,665	19,210	10,381	7,671	499
N (offpeak)	2,721	10,614	2,414	1,650	–
N (peak)	1,944	8,596	7,967	6,021	486

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors are clustered at day (t) and firm (i) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable (demeaned, unit MWh) is also specified but not reported in this table.

Table 7: Bid markup regression: firm group by generation mix

4.2.3 Bidding differences across hours: peak-hour bidding by firm group

Another way to verify differences in firms' bidding strategies is to examine whether the typical hourly bidding pattern observed in this market – where the bid markup tends to be higher in the peak hours than in the off-peak hours – is preserved in the post-increase sample. To do so, I compare bidding patterns between peak and off-peak hours within each pre- and post-increase samples. As discussed in Section 3.2.2, peak hours are when strategic considerations play a greater role in pricing and firms are most capable of exercising market power by increasing markups, whereas off-peak hours have much lower strategic capability. Therefore, firms – especially those engaging in strategic bidding – typically submit higher bids in peak hours than in off-peak hours.

I run equation (4) separately for pre- and post-increase samples, and by firm group, to check the general pattern of bid markups across hours within each sample. Only the bid markups of potentially marginal gas-fired units were used, similarly as before.

$$b_{ijth} - mc_{ijt} = \alpha + \beta \text{ Peak}_h \ + \gamma \text{ Demand}_{th} + \eta + \varepsilon_{ijth} \tag{4}$$

Results Table 8 presents the results for the firm size groups, showing that firms' bidding strategies across hours differ significantly between the pre- and post-increase samples. In the pre-increase sample (first row), overall bid markups are higher in peak hours, as shown in column (1). Within firm groups,

	(1)	(2)	(3)	(4)	(5)
	full Sample	Sub Sample: by Firm Size (MW)			
		< 100	[100, 500)	[500, 1000)	> 1000
		Fringe	Small	Medium	Large
	$b_{ij,th} - mc_{ij,t}$	$b_{ij,th}$	$b_{ij,th} - mc_{ij,t}$		
Pre-Increase					
Peak_h	0.786^{*}	0.743	0.689^{*}	0.599	0.898^{**}
	(0.389)	(0.905)	(0.382)	(0.486)	(0.352)
Post-Increase					
Peak_h	-0.103	-2.158	0.637	-0.014	-0.467
	(0.364)	(1.579)	(0.434)	(0.385)	(0.314)
Hour FE	x	x	x	x	x
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
N (Pre-Increase)	27,585	203	5,249	7,082	14,749
N (Post-Increase)	27,629	130	5,383	7,050	14,719

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Column (2) regression (fringe firms) uses the price bids (b_{ijth}) as a dependent variable due to the difficulty of estimating marginal cost (heat rates) for these units. Standard errors for regression (1) are clustered at the day (t) and firm (i) level, and standards errors for the subsample regressions (2)-(5) are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable (demeaned within each firm group, unit MWh) is also specified in the regression but not reported.

Table 8: Bidding differences: peak-hour bidding, firm group by size

shown in columns (2)-(5), large firms (column (5)) and small firms (column (2)) apply higher markups in peak hours than in off-peak hours. This pattern is consistent with the typical strategic bidding behavior documented in this wholesale electricity market, though it is not perfectly correlated with firm size, as medium-sized firms do not display a distinct bidding pattern.

In contrast, in the post-increase sample, shown in the second row of Table 8, peak-hour strategic bidding disappears. All firm groups, including both large and small firms that previously raised markups in peak hours, now exhibit no statistically significant difference in markups between peak and off-peak hours. This indicates a substantial change in firms' bidding strategies in the post-increase sample, particularly among the largest firms, which have the greatest capacity to behave strategically.

Differences in bidding patterns are more pronounced when firms are grouped by generation mix, as shown in Table 9. In the pre-increase sample (columns (2)-(5), first row), Gas Large, Gas/Oil Mix, and Other Mix firms tend to apply higher bid markups during peak hours, consistent with the typical strategic bidding pattern. This pattern is most pronounced among Gas Large firms, which can strategically utilize their substantial gas generation capacity during high-demand hours.

Interestingly, these patterns disappear in the post-increase sample, as shown in the second row of columns (2)-(5) in Table 9. Firm groups that previously increased markups during peak hours no longer exhibit this behavior in the post-increase sample. While overall markup levels may be higher across firm groups in the post-increase sample than in the pre-increase sample, the distinct peak-hour bidding patterns are absent, suggesting that firms' bidding and pricing strategies are more dispersed across hours. This indicates that firms' post-increase bidding strategies differ significantly from pre-increase strategies,

	(1)	(2)	(3)	(4)	(5)
	Full Sample	Sub Sample: by Firm Size			
		Heavy Base	Gas Large	Gas/Oil Mix	Other Mix
	$b_{ij,th} - mc_{ij,t}$	$b_{i,th} - mc_{ij,t}$			
Pre-Increase					
Peak_h	0.786^{*}	-0.205	1.049^{***}	0.732^{*}	0.727^{*}
	(0.389)	(0.760)	(0.379)	(0.396)	(0.401)
Post-Increase					
Peak_h	-0.103	0.457	-0.335	0.204	0.040
	(0.389)	(0.518)	(0.310)	(0.393)	(0.454)
Hour FE	x	x	x	x	x
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
N (Pre-Increase)	27,585	2,207	8,972	5,510	4,206
N (Post-Increase)	27,629	2,458	10,238	4,871	3,465

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors for regression (1) are clustered at the day (t) and firm (i) level, and standards errors for the subsample regressions (2)-(6) are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable (demeaned within each firm group, unit MWh) is also specified in the regression but not reported.

Table 9: Bidding differences: peak-hour bidding, firm group by generation mix

despite similar market fundamentals – such as demand, marginal costs, and the set of competitors – across samples.

4.3 Summary: Which firms show a change in bidding behavior?

There are several takeaways from these findings. First, higher post-increase price bids are more concentrated in peak hours, when strategic considerations typically play a greater role in bid formation, but also occur in off-peak hours for firms utilizing assets affected by cost changes during those periods. Second, the distinct peak-hour bidding patterns observed in the pre-increase sample disappear in the post-increase sample, accompanied by greater bid dispersion across hours and firms. This suggests that post-increase bidding strategies are not only systematically different from those in the pre-increase sample but also exhibit greater variation in how firms adjust their bids.

The results reveal differences in bidding strategies across firm types. Although firm size is often associated with higher markups and strategic bidding, the higher price bids in the post-increase sample are correlated not only with firm size but also with firms' strategic positions determined by their generation profiles. Gas Large and Gas/Oil Mix firms submit higher price bids in both off-peak and peak hours, suggesting that their post-increase strategies are spread more evenly across hours at a higher level, whereas Heavy base and Other Mix firms bid higher mainly in peak hours. These patterns appear correlated with the relative share of strategic assets in a firm's portfolio, a key feature that varies across firm groups based on generation mix.

Since market fundamentals remain unchanged across samples, the observed changes in bidding behavior likely reflect changes in firms' expectations about their competitors' strategies. In particular, the increased dispersion of bids and the overall rise in bid levels are consistent with firms anticipating a broader range

of competitor strategies, including higher price bids than in the pre-increase sample, which is analogous to firms facing greater uncertainty about how competitors will bid.

4.4 Discussion: Other possible causes

Markup adjustment In relation to the pass-through literature, where incomplete pass-through is often attributed to markup adjustment (e.g., exchange rate pass-through), asymmetric price responses could also be seen as another realization of markup adjustment. Yet, if two periods face identical marginal costs and market conditions, firms should apply the same markup on both. Explaining the observed price asymmetry through markup adjustment alone thus requires an additional rationale for why markups would be different between the pre- and post-increase samples – an asymmetry in incentives that is otherwise difficult to justify.

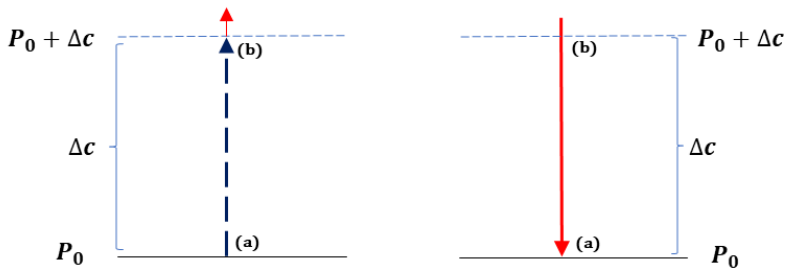
Tacit collusion Another possible explanation is tacit collusion, noted as one of the hypotheses in Borenstein et al. (1997). That is, prices may be sticky downward because the past prices serve as a focal point for oligopolistic sellers, as firms need not immediately adjust their prices to a negative cost shock. Coordination could then emerge naturally and persist until a firm observes a decline in sales or a price drop below the trigger level.

Based on the understanding of how tacit collusion emerges and is sustained, my empirical setting is unlikely to support its formation. The post-increase periods in my data, which do not exceed a week, are relatively short for tacit collusion to develop. Moreover, firms cannot immediately observe competitors' bids or pricing decisions in previous periods, as this information is released only after four months. While equilibrium price and quantity data are available daily, this information alone does not reveal strategies of competitors in this uniform-price auction setting.[35] Price leadership is also difficult to emerge because firms submit bids simultaneously each day rather than sequentially. Even if some firms attempt to lead by raising price bids, others cannot observe these changes, making it difficult to distinguish strategic pricing from fluctuations in market fundamentals.[36] Lastly, the static nature of strategic interaction and the stochastic variation in market conditions within the sample, as shown in Section 2.3, further complicate the formation of a focal point and the emergence of collusion.

The results of my analysis further support the claim that the observed patterns are not driven by tacit collusion. If firms were attempting to collude to increase market power, they would do so more effectively when the detection of collusion is less likely and their relative market power is greater. This implies that coordination towards higher prices should appear especially during peak hours, resulting in increased differences between peak and off-peak bidding patterns. However, I find that the distinction between peak and off-peak bidding becomes weaker in the post-increase sample, with firms submitting higher price bids not only in peak but also in off-peak hours. Moreover, the bidding pattern is far from converging on a focal point: price bids in the post-increase sample become more dispersed across firms

[35] Firms receive daily notifications of their dispatched quantities and market prices after the market clears but do not see competitors' bids or generated quantities. The bids submitted by firms are released four months later per FERC regulations.

[36] For instance, Byrne and de Roos (2019) show that in the retail gasoline market, where price adjustments are publicly visible, reaching a focal point can take over a year of repeated interactions, with price leadership playing a crucial role. Identifying tacit collusion empirically remains challenging, particularly in determining which price becomes the focal point and how firms coordinate.



(a) Cost increase by Δc (b) Cost decrease by Δc

Figure 6: Rationalizable strategies under cost Increase and cost decrease cases

and hours. Furthermore, the overall price difference between pre- and post-increase samples is not large enough to be support collusion. Appendix A.3.2 provides further discussion of other possible causes (e.g., forward contract and fixed costs).

5 Belief and Strategy Differences as Sources of Asymmetric Price Responses

5.1 Asymmetry in the strategy set by the direction of the cost change

As discussed in Section 2.4, the empirical setting of this paper allows me to exclude many potential factors that could cause an asymmetric response. Therefore, if any difference in price responses exists, it can be attributed to supply-side behavior in a non-cooperative strategic environment. Supporting this, the bidding analysis in Section 4 shows that firms adopt different bidding strategies in the post-increase sample, which appears more dispersed and less patterned than in the pre-increase sample.

To understand this phenomenon, I focus on the differences in strategy sets between the cost-increase and cost-decrease cases, which are associated with firms' beliefs. Firms' beliefs about competitors' strategies are shaped by the competitive environment, implying that strategic uncertainty can vary across situations.[37] A change in input costs represents a shift in the competitive environment that can prompt firms to revise their beliefs over strategy sets. Although competition in this market is largely static, there is an intertemporal component to belief formation: by observing gas prices in the previous and current periods, firms can infer the direction of cost changes – whether costs are rising or falling – and revise their beliefs about the strategic environment accordingly. Thus, differences in beliefs imply differences in the rationalizable strategy sets supported by those beliefs.

I demonstrate that these rationalizable strategy sets inherently differ by the direction of the cost change: under a cost decrease, the set of rationalizable strategies is wider than under a cost increase. This asymmetry in strategy sets implies that downward cost movements are associated with greater strategic uncertainty than upward movements.

To fix ideas, suppose firms initially charge a price P_0 when marginal cost is c_0, with an initial markup of zero. When cost increases by Δc, from c_0 to $c_1 (= c_0 + \Delta c)$, it is common understanding that every

[37] Strategic uncertainty can affect market outcomes, particularly in cases where multiple equilibria exist. For further discussion, see Morris and Shin (2002), Huyck et al. (1991), among others. Empirical studies have examined strategic uncertainty in the contexts of new market entry (Doraszelski et al., 2018) and uncertainty related to distant competitors' entry or exit (Aguirregabiria and Magesan, 2020).

firm must raise its price by at least Δc to maintain per-unit profitability. Raising the price by less than Δc results in a profit loss per unit sold, regardless of competitors' pricing decisions, and competitors would rationally expect the firm to increase its price by at least that amount. Therefore, any price below $P_0 + \Delta c$, i.e., $P_1 \in [P_0, P_0 + \Delta c)$, can be rationally excluded (strictly dominated) from the firm's strategy set, as such prices do not cover the increased marginal cost. Prices above this threshold, i.e., $P_1 \in [P_0 + \Delta c, \infty)$, reflect purely strategic considerations and belong to the firm's rationalizable strategy set. Given this set, firms are likely to pass through the cost increase fully or to a large extent. Figure 6 Panel (a) depicts this upward cost change situation.

On the other hand, when costs decrease, a firm's profit increases if everything else remains constant. Therefore, whether firms lower their prices is entirely a strategic decision, not driven by the need to avoid losses from cost changes. For example, suppose a firm's current price is $P_1 = P_0 + \Delta c$ and cost decreases by Δc, from c_1 to $c_0 (= c_1 - \Delta c)$. The marginal cost reduction immediately increases the firm's per-unit margin, unless competitors also lower their prices. The firm will reduce its price only if it believes competitors to do so, in which case the profit loss arises from reduced residual demand. Thus, the expected profits associated with prices (strategies) in the range $P \in [P_0, P_0 + \Delta c]$ depend critically on competitors' strategies. Depending on firm's beliefs, setting a price in this range is not rationally excluded from the firm's strategy set, meaning that prices yielding incomplete pass-through is part of the rationalizable strategy set. Figure 6 Panel (b) depicts this downward cost change situation.

This simple example demonstrates that the set of rationalizable strategies differs depending on whether the firm's cost increases or decreases, highlighting the asymmetry in strategy sets.[38] When cost rises from c_0 to c_1, any price adjustment smaller than Δc is strictly dominated, leaving $P \in \left[P_0 + \Delta c, \bar{P}\right]$ as the rationalizable strategies. When cost decreases from c_1 to c_0, only prices below P_0 are strictly dominated. Any price in the range $P \in [P_0, P_0 + \Delta c]$ could be a best response to some belief about the competitor's strategy – for example, to a belief that the competitor may not reduce its price fully. Since rationalizability does not require beliefs be correct, these strategies are not strictly dominated. Thus, more strategies remain rationalizable compared to the cost-increase case.

While this example assumes an initial markup of zero (denoted as $\tilde{m} = 0$), the asymmetry persists even with a positive initial markup ($\tilde{m} > 0$). Unlike in the zero-markup case, a positive initial markup allows firms to sustain a cost increase without raising prices. The maximum per-unit profit loss a firm can absorb without altering the price is bounded by its initial markup, $\tilde{m}$ (or $\Delta\pi \leq \tilde{m}\tilde{q}$). Conversely, when costs decrease, the per-unit markup immediately rises by Δc without any price adjustment, making the firm's markup $\tilde{m} + |\Delta c|$. Firms will lower prices only if they believe competitors will do so, but even then, they can continue to avoid lowering the price longer than in the cost-increase case, as they can sustain a per-unit profit loss up to $\tilde{m} + |\Delta c|$ (or $\Delta\pi \leq (\tilde{m} + |\Delta c|)\tilde{q}$).

[38] The set of strategies that can be supported as best responses to some belief about competitor's strategy is termed the rationalizable strategies (Bernheim 1984; Pearce 1984). Practically, this refers to strategies that survive the process of iterated elimination of strictly dominated strategies. A firm may assign a probability distribution over its competitor's strategies, and any strategy to which it assigns positive probability is one it believes could possibly be played by the competitor, as the strategy has not been eliminated as strictly dominated. The firm's own rationalizable strategies, then, consist of best responses to such beliefs. Importantly, these beliefs do not have to be correct in the sense of matching the actual strategy of the competitor (i.e., consistency); rationalizability only requires that each strategy be optimal under *some belief*.

5.2 Equilibrium Concepts

This reasoning in Section 5.1 does not depend on any particular equilibrium concept. Regardless of the type of game or solution concept employed, a cost increase versus a cost decrease leads to different rationalizable strategy sets, thereby shifting the domain from which any equilibrium strategy must be drawn. Depending on the configuration of the game – that is, the underlying behavioral assumptions and structural features – different equilibrium outcomes are possible, some consistent with the paper's empirical setting and others not. For example, the simplest symmetric Bertrand model, where infinite rounds of belief updating yield a unique Nash Equilibrium, cannot rationalize empirical observations in which different pricing outcomes emerge in the cost-decreasing phase. Likewise, models assuming a dynamic repeated-game structure, such as collusion models, do not fit this market, where the relevant environment is a repeated static game with stochastically evolving state.

For this market, the most relevant model would be a multi-unit uniform-price auction, which is known to admit multiple Bayesian Nash Equilibria (BNE). Thus, the documented asymmetry in price responses across cost-increasing and cost-decreasing samples could reflect a shift from one equilibrium to another. If so, analyzing the rationalizable strategy sets clarifies how the broader range of strategies in the cost-decreasing phase allows different equilibrium beliefs and outcomes to emerge.

However, the comparison between cost-increase and decrease situations need not be limited to equilibrium beliefs. Based on the concept of rationalizability, the subjective belief that makes the observed choice a best response can be inferred. These subjective beliefs need not be correct in the sense of being equilibrium beliefs.

Therefore, throughout the analysis, I do not commit to a specific equilibrium model. Doing so would revert the analysis to the earlier challenge of explaining the asymmetry in price responses within a particular theoretical framework, which has proven difficult. Instead, I estimate beliefs and strategy sets by leveraging the fact that observed choices are best responses, without imposing equilibrium restrictions. The idea behind this approach is similar to estimation methods that rely on best-response conditions rather than equilibrium assumptions (e.g., Hailey and Tamer 2003).[39] In the electricity market, this approach benefits from the fact that marginal costs are relatively transparent and can be accurately measured from the data, which further facilitates estimation of primitives without equilibrium restrictions (see Section 6).

Because estimation based on the best-response condition is feasible regardless of whether the observed choices or underlying strategies arise from equilibrium, non-equilibrium models are not ruled out. Indeed, non-equilibrium frameworks such as the level-k model or fictitious play have been studied in the context of electricity markets (Hortaçsu et al., 2019; Doraszelski et al., 2018). However, I do not attempt to determine whether observed behavior is better explained by equilibrium or non-equilibrium models, or which non-equilibrium framework would be most appropriate, given the difficulty of model selection.[40]

To summarize, I do not attempt to identify which specific equilibrium or non-equilibrium model explains the observed outcomes. This is not a limitation, because the goal of the paper is not to determine

[39] In addition to Hailey and Tamer (2003), estimation methods of Bajari et al. (2007) and Pakes et al. (2015) also rely on inequality conditions implied by necessary condition of best-response behavior. These papers apply estimation method that do not require committing to one particular model to interpret the observed outcomes, which is especially valuable in settings with multiple equilibria or ambiguous equilibrium selection.

[40] See Appendix A.4.1 for further discussion.

the best-fitting equilibrium model, but rather to show that the strategy sets rationalizing observed choices differ across cost regimes – differences that may contribute to, or correlate with, the cost response asymmetry I find. The estimated belief may reflect any stage of iterative reasoning or level of strategic sophistication. My objective is to recover the belief that makes the observed bid a best response – whether it arises from full equilibrium reasoning, limited strategic sophistication, or some other behavioral process. This framework therefore accommodates a broad range of belief formation mechanisms consistent with observed behavior.

6 Belief Estimation

In this section, I estimate firms' beliefs, which I model as ex ante bid distributions, and analyze how beliefs and strategy sets differ between the pre- and post-increase samples. Specifically, I estimate firms' beliefs about competitors' strategies that rationalize the observed bids as best responses, without committing to any particular equilibrium concept (as discussed in Section 5.2). The only maintained assumption is that firms choose bids that maximize expected profit given their beliefs. This approach allows me to exploit the necessary condition of profit maximization in estimation, while avoiding strong assumptions about the equilibrium governing the pre- and post-increase outcomes.

Relaxing the equilibrium assumption is feasible in this setting because I do not need to jointly estimate other structural primitives, such as marginal costs, alongside beliefs. In the nonparametric estimation of auction models (e.g., Guerre et al. 2000; Hortaçsu and McAdams 2010), researchers impose a Bayesian Nash Equilibrium assumption to infer ex-ante beliefs (or the distribution of competitor valuations) from observed bids. This assumption is necessary to account for the uncertainty firms face about competitors' bids while simultaneously identifying other primitives of the model. However, in the electricity market, the marginal costs of electricity generators can be treated as known parameters, since they can be accurately measured from the data. This feature allows me to estimate the ex ante subjective distribution of beliefs over competitors' bids without relying on equilibrium conditions to map observed bids to beliefs.

Optimal Bidding Model I present a model that characterizes a firm's bidding decisions in a multi-unit uniform auction, adapted to the wholesale electricity market context.[41] Suppose there are $i = \{1, \ldots, N\}$ firms that each operates J_i number of units, indexed by $j = \{1, \ldots, J_i\}$, that can generate electricity using multiple energy sources. In the day-hour auction, a firm submits hourly price bids (b) and quantity bids (q) – which consist of multiple steps (k) of bids – for each of its generating units.

Given the market-clearing price P_{th}, the (ex-post) profit function of firm i in day t, hour h auction is:

$$\pi_{ith}(\mathrm{b}_{ith}, \mathbf{b}_{-ith}) = P_{th}(\mathrm{b}_{ith}, \mathbf{b}_{-ith}) \left(Q_{ith}(P_{th}(\mathrm{b}_{ith}, \mathbf{b}_{-ith}))\right) - \sum_{j=1}^{J_i} C_{ijt}(\, q_{ijth}(P_{th}(\mathrm{b}_{ith}, \mathbf{b}_{-ith}))\,) \tag{5}$$

where b_{ith} denotes firm i's bid vector across its units, and $\mathbf{b}_{-ith}$ collects bid vectors of all other firms. Q_{ith} is the total quantity generated by firm i's dispatched units, and q_{ijth} is the output of unit j of firm i, both of which depend on the market price $P_{th}(\mathrm{b}_{ith}, \mathbf{b}_{-ith})$, a function of the bid distribution.[42] Following

[41] The model presented here is the closest to that used in Kim (2022), Reguant (2014), Ryan (2021), and Wolak (2007).

[42] Forward-contracted quantity is omitted from the generation quantity for simplicity, though it is included in the estimation.

the literature, the generation cost of unit j of firm i is assumed linear in quantity, $C_{ijt}(q_{ijth}) = mc_{ijt}q_{ijth}$, implying a constant marginal cost $C'_{ijt}(q_{ijt}) = mc_{ijt}$.

Since firms submit bids simultaneously in the auction, they face uncertainty over competitors' bids ($\mathbf{b}_{-ith}$). Thus, a firm forms a *belief* about the distribution of others' bids ($\widetilde{\mathbf{b}}_{-ith}$) and chooses the optimal bid, b_{ith}, that maximizes its ex-ante expected profit given this belief. The maximization problem of firm i is described below, where the expectation is taken over $\widetilde{\mathbf{b}}_{-ith}$:

$$\max_{\mathrm{b}_{ith}} \ \mathbb{E}_{-ith}[\ \pi_{ith}(\mathrm{b}_{ith}, \widetilde{\mathbf{b}}_{-ith})\ ]$$

Because firms lack incentives to bid strategically when they cannot influence the price, the optimality condition applies only to their ex-ante marginal units with a positive probability of setting the market price.[43] Although only one unit sets the price ex-post, multiple ex-ante marginal units can exist in a single auction due to uncertainty over competitors' bids and the market clearing price.

Given that the step k bid of firm i's unit j, denoted $\mathrm{b}_{ijkth} = \langle b_{ijkth}, q_{ijkth} \rangle$, is an ex-ante marginal unit in auction th, the necessary first-order condition of profit maximization is shown below in equation (6). This condition applies to firms that anticipate their bid, b_{ijkth}, to be the market-clearing price ex ante.

$$\mathbb{E}_{-ith}\left[\frac{\partial P_{th}}{\partial b_{ijkth}}\left[\ (Q_{ith}(P_{th}))\ +\ \left(b_{ijkth} - \ mc_{ijt}\right)\frac{\partial RD_{ith}}{\partial P_{th}}\ \right]\right] = 0 \tag{6}$$

Rearranging Equation (6) yields Equation (7), which expresses a firm's price bid as marginal cost plus a strategic component, the bid markup.

$$\text{bid markup}_{ijth} = b_{ijkth} - mc_{ijt} \ = -\ \frac{\mathbb{E}_{-ith}[\frac{\partial P_{th}}{\partial b_{ijkth}}\ Q_{ith}\ ]}{\mathbb{E}_{-ith}[\frac{\partial P_{th}}{\partial b_{ijkth}}\ \partial RD_{ith}/\partial P_{th}\ ]} \tag{7}$$

In electricity markets, marginal cost of electricity generation, mc_{ijt}, can be measured using available data, a feature exploited in many studies (Wolfram, 1998; Hortaçsu and Puller 2008; Hortaçsu et al. 2019). As a result, the bid markup in equation (7) can be observed from the data and becomes a function of firms' subjective beliefs about competitors' bids, $\widetilde{\mathbf{b}}_{-ith}$. That is, the bid markup depends on the expected slope of the firm's residual demand and the firm's expected quantity – both functions of firm i's ex ante beliefs, $\widetilde{\mathbf{b}}_{-ith}$, which determine the expectation terms $\mathbb{E}_{-ith}(\cdot)$.

Estimation of beliefs about the competitors' bids I implement a simulated method of moments (SMM) estimation using the hour-day bids submitted by firms and generating units to estimate firms' beliefs. The high-frequency bidding data provide rich variation in bid markups both within and across firms. I construct a moment condition such that the expected difference between the observed and simulated bid markups is zero. Because the expectation over $\widetilde{\mathbf{b}}_{-ith}$ must be approximated via simulation, the estimation becomes a simulated method of moments (Pakes and Pollard, 1989).

The objective is to estimate parameters of the belief distribution of competitors' bids that rationalize firm i's optimal bids of its ex-ante marginal units. Firm i's belief distribution for each competing unit is

[43] Analytical expression of the probability of being ex-ante marginal unit, $\frac{\partial P_{th}}{\partial b_{ijkth}}$, available in the Online Appendix B.1.1.

parameterized as a log-normal distribution, consistent with existing simulation-based empirical auction studies (Laffont et al. 1995, Cantillon and Pesendorfer 2006, and etc.) and is supported by the data.[44]

Estimation method In each hour-day market (t,h), firm i faces a set of competitors indexed by $m = 1,\ldots,M$. The price bids of competitors of firm i is $\mathbf{b}_{-ith} = \{b_1, b_2, \ldots, b_M\}$ with corresponding quantity bids $\{q_1, q_2, \ldots, q_M\}$. Throughout the analysis, quantity bids are fixed at the observed levels in market (t,h), as participants tend to adjust mainly the price bids when bidding.

The uncertainty about competitors' strategies implies that firm i forms a distribution over $\widetilde{\mathbf{b}}_{-ith}$, with draws from this distribution indexed by $s = 1,\ldots,S$:

$$\widetilde{\mathbf{B}}_{-ith} = \left[\widetilde{\mathbf{b}}^1_{-ith} \quad \widetilde{\mathbf{b}}^2_{-ith} \quad \ldots \quad \widetilde{\mathbf{b}}^S_{-ith}\right]^\top, \quad \widetilde{\mathbf{b}}^s_{-ith} = (b^s_{i,1},\ldots,b^s_{i,M})$$

I assume that firm i's belief about the distribution from which competitor m's bid is drawn follows a log-normal distribution, *i.e.*, $\phi_{i,m} : ln(b_{i,m}) \sim N(\mu_{i,m}, \sigma^2_{i,m})$.[45] Then, the bid vector of competitors generated from the s draw is given by:

$$\widetilde{\mathbf{b}}^s_{-ith} = [\exp(\mu_{i,1} + \sigma_{i,1}Z^s_1),\ldots,\exp(\mu_{i,m} + \sigma_{i,m}Z^s_m),\ldots,\exp(\mu_{i,M} + \sigma_{i,M}Z^s_M)]$$

with each standard normal draw of $\mathbf{Z}^s = [Z^s_1,\ldots,Z^s_M]$ producing one realization of $\{b^s_{i,m}\}^M_{m=1}$.

For each simulated bid vector $\widetilde{\mathbf{b}}^s_{-ith}$, I compute the corresponding bid markup using equation (7), conditioning on firm i believing that the price bid of its marginal unit sets the ex-post market price (i.e., $P_{th} = b_{ith}$). Specifically, the simulated bid pairs $\langle b^s_{i,m}, q_m\rangle$ are ordered by increasing values of $b^s_{i,m}$ to form firm i's residual demand. I then compute the slope of the residual demand, $RD'(\widetilde{\mathbf{b}}^s_{-ith}; P_{th} = b_{ith})$, and total output, $Q_{ith}(\widetilde{\mathbf{b}}^s_{-ith}; P_{th} = b_{ith})$.[46]

This procedure is repeated for each simulation draw $s = 1,\ldots,S$, using $S = 500$ draws, generating simulated bid vectors $\{\widetilde{\mathbf{b}}^1_{-ith},\ldots,\widetilde{\mathbf{b}}^S_{-ith}\}$. The simulated bid markup of firm i in market (t,h) is then computed as follows:

$$\text{bid markup}^{sim}_{ith} = \frac{\mathbb{E}_{-it}[Q_{ith}(\widetilde{\mathbf{b}}^s_{-ith}; P_{th} = b_{ith})]}{E_{-it}[RD'_{ith}(\widetilde{\mathbf{b}}^s_{-ith}; P_{th} = b_{ith})]} \tag{8}$$

,where details on how the expectation terms $\mathbb{E}_{-it}$ are approximated can be found in Appendix A.5.1.

Selection of a Competitor Set Although strategic uncertainty includes uncertainty about competitors, I treat this information as fairly predictable and therefore do not endogenize the set of potential competitors in the estimation. Instead, I use the competitor set from the day-hour observation that most closely resembles the candidate (t,h) market, implicitly assuming that firms form beliefs based on past

[44] Figure B4 in the Online Appendix shows that the log-transformed bid prices of a generating unit are approximately normally distributed.

[45] To alleviate computational burden, I assume uncorrelated bid belief distributions across competitors – an independence restriction commonly imposed in private-value auction settings. Also, I assume no correlation of beliefs among multiple units owned by the same firm as only one generating unit of a firm appears as a competitor in each market (t,h).

[46] The slope RD' is obtained by fitting a linear specification to the logged price bids ($ln(b_{i,m})$) and corresponding quantity bids (q_m). This linear approximation is appropriate because only a small number of close competitors (five units on average) are used, making the slope a local estimate. To ensure that the marginal bid of firm i is close to the ex-post equilibrium price, I restrict (t,h) to markets in which firm i's marginal bid lies within ± \$5/MWh of the ex-post equilibrium price.

days with similar market conditions. A similar day-hour $(\bar{t}, \bar{h})$ is selected from the pre-increase sample based on the closeness of daily gas prices, daily demand, hour, real-time demand, and daytime.[47]

Given the selected similar day-hour $(\bar{t}, \bar{h})$, I identify close competitors for each candidate market (t, h) as follows.[48] First, firm i's residual demand curve, $RD_{i\bar{t}\bar{h}}$, is constructed using the ex-post bids observed in market $(\bar{t}, \bar{h})$. I then select the set of close competing units m in market (t, h), denoted $u^i_{m,th}$, for $m = 1, \ldots, M$. Each competing unit corresponds to a firm-generator-step combination chosen based on its proximity to the ex-post equilibrium point of $RD_{i\bar{t}\bar{h}}$.[49] In the analysis, I select $M = 5$ close competing units for each firm i in the candidate market (t, h).

Estimation The moment condition used for estimation is the difference between the simulated bid markup shown in Equation (8) and the observed bid markup, denoted bid markup$^{obs}_{ith}$, in market (t, h). The sample mean of this difference averaged across days $(t = 1, \ldots, T)$ for a given hour h is:

$$\bar{g}^h_{i,T}(\theta_i) = \frac{1}{T} \sum_{t=1}^{T} \left[\text{bid markup}^{sim}_{ith}(\theta_i) - \text{ bid markup}^{obs}_{ith} \right]$$

I estimate the parameters of the belief distributions only for a subset of competitors, denoted u^i_l (where $l = 1, \ldots, L$), selected based on the frequency with which each competitor appears in the estimation sample. Therefore, although firm i has M competitors in each (t, h) market, denoted $U^i_{th} = \{u^i_{1,th}, \ldots, u^i_{M,th}\}$ for $t = 1, \ldots, T$ and $h = h_1, \ldots, h_H$, only a fixed set of competitors, $U^i = \{u^i_1, \ldots, u^i_l, \ldots, u^i_L\}$, is parameterized and estimated for each firm i. For competitors whose bids are not parameterized, I use bid data from a similar market $(\bar{t}, \bar{h})$, implicitly assuming that firm i's beliefs about these unparameterized competitors are known with certainty (i.e., degenerate at their ex-post bids).

The parameter set for firm i is $\theta_i = \{\mu_{i,1}, \ldots, \mu_{i,L}, \sigma_{i,1}, \ldots, \sigma_{i,L}\}$. The moment conditions and objective functions are as follows:

$$\bar{g}_{i,T}(\theta_i) = \begin{bmatrix} \bar{g}^{h_1}_{i,T}(\theta_i) \\ \bar{g}^{h_2}_{i,T}(\theta_i) \\ \vdots \\ \bar{g}^{h_H}_{i,T}(\theta_i) \end{bmatrix}$$

and,

$$\hat{\theta}_i = \underset{\theta_i}{\text{argmin}} \;\; \bar{g}_{i,T}(\theta_i)' \, W_T \, \bar{g}_{i,T}(\theta_i)$$

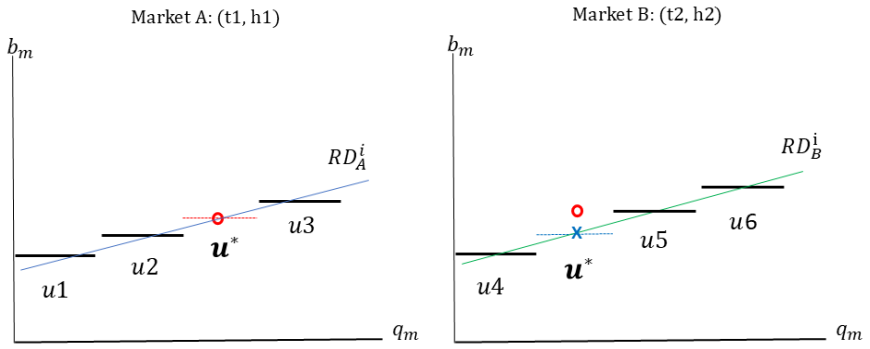
where W_T is the optimal GMM weighting matrix.

I estimate θ_i separately for off-peak hours ($H_{\text{off-peak}}$) and peak hours (H_{peak}), and for the pre-increase (T_{pre}) and post-increase (T_{post}) samples. Different numbers of competitors are parameterized for each sample: $L_{\text{off-peak}} = 4$ for the off-peak-hours sample ($h \in H_{\text{off-peak}}$), and $L_{\text{peak}} = 5$ for the peak-hours sample ($h \in H_{\text{off-peak}}$). Consequently, four sets of parameters are estimated across the combinations of $t \in \{T_{pre}, T_{post}\}$ and $h \in \{\text{off-peak}, \text{peak}\}$: $\{\theta_{i,pre}, \theta_{i,post}\}_{h \in \text{off-peak}}$ and $\{\theta_{i,pre}, \theta_{i,post}\}_{h \in \text{peak}}$.

[47] For a sample $(t, h) \in$ Post Increase, the similar day-hour market is selected from pre-increase sample days. For a sample $(t, h) \in$ Pre-Increase, the similar market is also chosen from pre-increase sample, but only from those prior to the candidate (t, h) (i.e., $\bar{t} \leq t$).

[48] See Appendix A.5.2 for a summary of competitors.

[49] Since the smallest bidding unit in this auction is a step, each firm-generator-step can be treated as an independent unit.



(a) Market A: $(t1, h1)$ observation (b) Market B: $(t2, h2)$ observation

Figure 7: Identification: Variation in Residual Demand and Competitors

Identification Several assumptions enable the identification of parameters. First, I restrict the number of competitors drawn from parameterized distributions (L) to satisfy the order condition, which requires that the number of parameters ($2L$) not exceed the total number of hours in the sample. I estimate $L_{\text{off-peak}} = 4$ and $L_{peak} = 5$ competitors for the peak and off-peak hour samples, respectively.

Second, I assume that firm i's belief distribution for each parameterized competing unit, u_l^i, is constant throughout the sample. This assumption relies on the fact that days in the sample are similar in fundamentals (e.g., marginal costs), and that expectations about competitors' bids should not differ significantly across days and hours of similar conditions. To ensure homogeneity in beliefs, I divide the sample into more homogeneous groups based on pre- and post-increase periods, as well as peak and off-peak hours, and estimate parameters separately for each group.

Third, I assume that the expected set of close competitors a firm faces in market (t, h) is derived from information of a similar past day-hour market $(\bar{t}, \bar{h})$. Instead of using the ex-post close competitors of (t, h), I construct the residual demand for the similar market and extract the corresponding set of close competitors. This approach mimics the firm's belief formation process, in which firms rely on information from past markets when making bidding decisions.

Identification relies on observing variations in firm i's bid markups, the set of competitors U_{th}^i, and their bid values $b_{m,th}$ (where $m \neq l$), across day (t) and hour (h) markets in which the parameterized competitor u_l^i appears as a close competitor. Variation in firm i's bid markups reflect variation in the expected residual demand slopes, which is the average outcome of the firm's belief distribution. Identifying the mean ($\mu_{i,l}$) and dispersion ($\sigma_{i,l}$) of the belief distribution for u_l^i requires observing variation in firm i's bid markups across markets where the same competitor u_l^i appears as part of U_{th}^i, but alongside different sets of other competitors. Variation in the set of competitors other than the parameterized unit – namely, $u_{m,th}^i$ $(m \neq l)$ when $u_l^i \in U_{th}^i$ – is particularly important for identification.

Figure 7 illustrates the identification strategy with a simple example. Panels (a) and (b) show firm i's set of competitors, U_{th}^i, where unit u^* is the only parameterized competitor, and the corresponding (reversed) residual demand (RD_{th}^i), in market A (day $t1$, hour $h1$) and market B (day $t2$, hour $h2$), respectively.

In market A, firm i's competitor set is $U_A^i = \{u_1, u_2, u_3, u^*\}$. The average price bid of unit u^*, $\bar{b}_A^*$ (red circle in panel (a)), is identified by choosing the ordering of competitors and the (average) bid value

Variable	Mean	Min	Median	Max	Std. Dev.
$\hat{\mu_{i,l}}$	3.5186	2.7068	3.5215	4.1276	0.1603
$\hat{\sigma_{i,l}}$	0.0147	0.0001	0.0032	0.1874	0.0302
Price bid Mean	3.5538	3.2933	3.5616	4.0444	0.1735
Price bid S.D.	0.1033	0.0607	0.0919	0.1816	0.0388

Notes: Summary statistics of the distribution parameter estimates (θ_i) at the competing unit level (u_l^i) are presented in the first two rows of the table. In the last two rows, I compute the mean and standard deviation of the competing unit's price bids during the sample period and report the summary statistics.

Table 10: Parameter Estimates and Bid Data Comparison: Summary Statistics

b^* that minimize the difference between the bid markup implied by the slope of RD_A^i and the observed bid markup. If only the mean (μ) is of interest, it can be identified from this single market observation. However, identifying both μ and σ from a single observation is not feasible, since different (μ, σ) pairs can generate the same expected average bid consistent with the observed residual demand. For example, the identified average bid value could be rationalized by a degenerate distribution with parameter $(\mu, 0)$ or by a distribution with $(\tilde{\mu}, \tilde{\sigma})$.

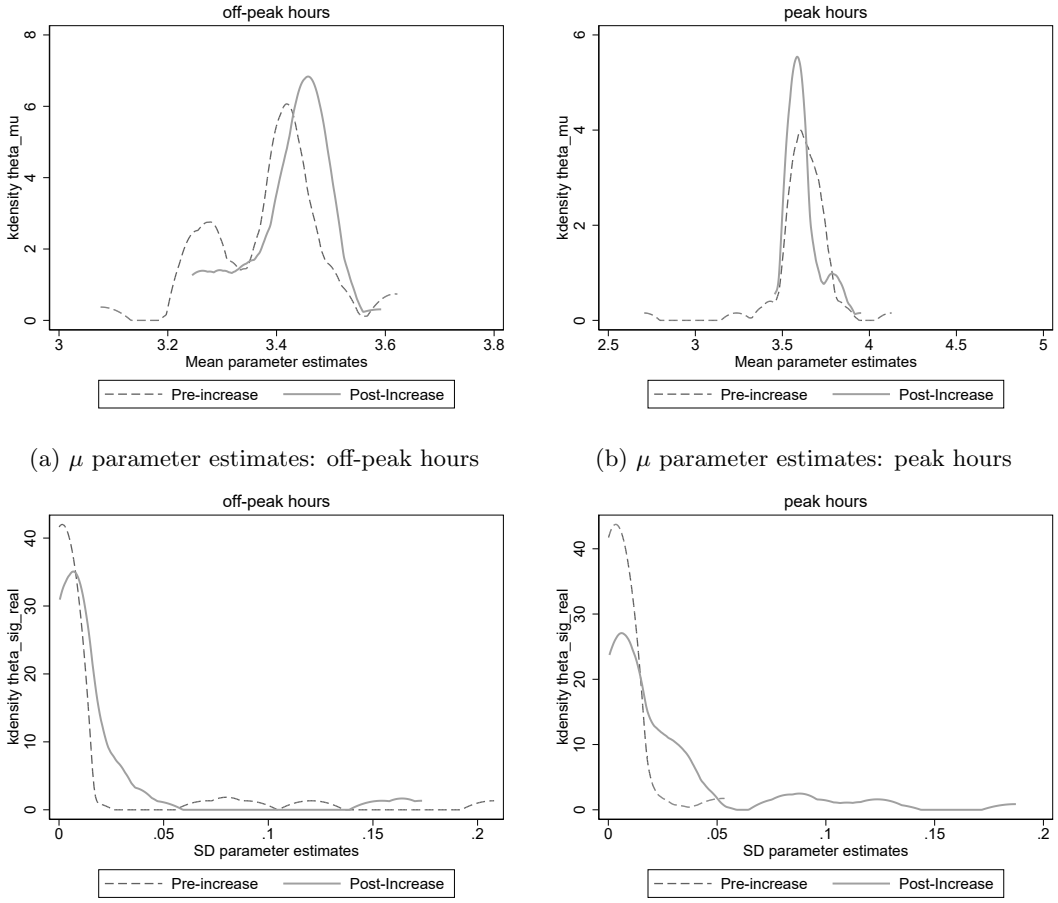
This problem can be resolved by observing the outcome of another market, market B, where firm i faces a different competitor set, $U_B^i = \{u_4, u_5, u_6, u^*\}$, which also includes the parameterized unit u^*. Different set of competitors, together with firm i's bid markup, identifies the average price bid of unit u^*, $\bar{b}_B^*$ (blue cross in panel (b)) as the value that minimizes the difference between the bid markup implied by RD_B^i and the observed bid markup. The intuition behind the identification is as follows. Suppose a distribution with parameter $(\mu, 0)$ that rationalizes market A's outcome implies an average bid – shown as a red circle in panel (b) – that does not coincide with $\bar{b}_B^*$, shown as a cross in panel (b). This second observation therefore identifies the existence of σ and determines its magnitude at the same time. Observing multiple markets in which u^* appears as a competitor, alongside varying sets of other competing units, allows me to uniquely identify both μ and σ.

Therefore, conditioned on the assumptions demonstrated earlier, identification of (μ, σ) relies on observing multiple markets in which the parameterize unit u^* competes with varying sets of competitors, variations in their bid values, and firm i's optimal bid markups across hours and days. The electricity market provides such variation because hourly demand levels are determined exogenously outside the wholesale market. This exogenous variation in demand, in turn, generates changes in competitor sets. Moreover, even though the hourly market environment changes with demand, it is always possible to find a marginal unit of firm i and its optimal bid markup at any demand level, since firm i can employ multiple units for strategic bidding.

6.1 Results

I estimate separate set of parameters for each firm i, $\theta_i = \{\mu_{i,1}, \ldots, \mu_{i,L}; \sigma_{i,1}, \ldots, \sigma_{i,L}\}$, for the pre- and post-increase samples, and for off-peak and peak hours. Although it is difficult to evaluate model fit given that the estimates represent subjective belief distributions, I compare the estimates to the mean and standard deviation of actual price bids of the corresponding competing unit, shown in Table 10, and find that the estimates fall within a reasonable range.

Figure 8 presents the distribution of estimates $\hat{\theta}_{i,\text{Pre}}$ and $\hat{\theta}_{i,\text{Post}}$, plotted separately for off-peak and



(a) μ parameter estimates: off-peak hours

(b) μ parameter estimates: peak hours

(c) σ parameter estimates: off-peak hours

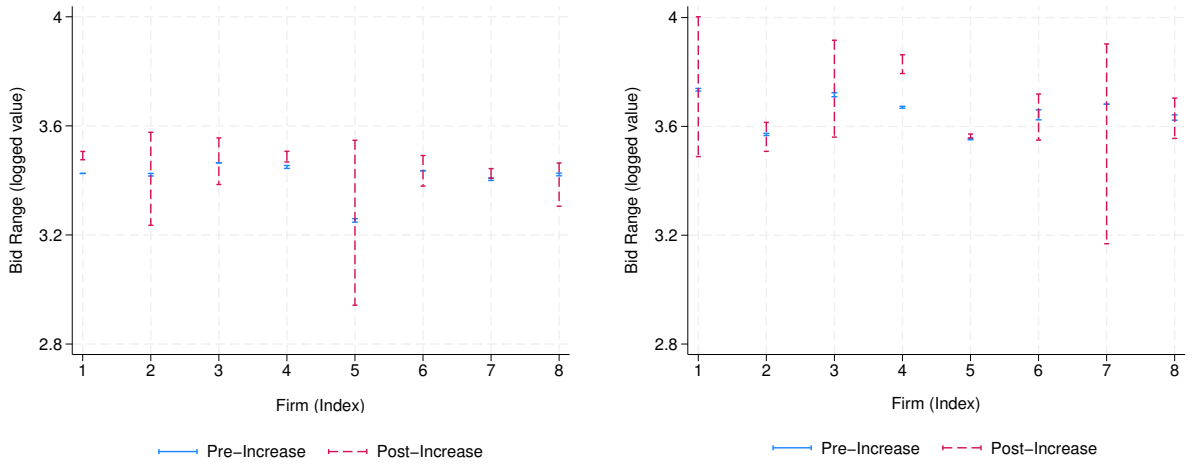
(d) σ parameter estimates: peak hours

Figure 8: Mean and Standard Deviation Estimates: Pre- and Post-Increase Samples

peak hours. Panels (a) and (b) show the mean parameter (μ) estimates of firms' belief distributions, with estimates being slightly larger in the post-increase sample (indicated by a rightward shift in the distribution) than in the pre-increase sample. A more distinct difference is observed in the standard deviation parameter estimates, shown in panels (c) and (d). The distribution of $\hat{\sigma}$ in the pre-increase sample is more concentrated around lower values in both off-peak and peak hours, indicating little dispersion in firms' belief distributions. However, in the post-increase sample, the estimates are more spread out toward higher values, particularly during peak hours. This suggests that belief distributions in peak hours are more dispersed in the post-increase sample than in the pre-increase sample.

To show how much of these parameter differences translate into bid range differences, Figure 9 plots the range of price bids of a firm's competitor that showed the largest increase in the bid dispersion – a single competitor with the highest increase in σ parameter among the list of competitors of firm i (indicated with firm index).[50] I plot the 95% range of the selected competitor's logged price bids ($ln(b_{i,l})$) for both pre- and post-increase samples, separately for off-peak and peak hour samples shown in panel (a) and (b), respectively. The bid ranges of these selected competitors become wider in the post-increase

[50]Figure A3 in the Appendix shows the same graph, overlaid with the competitors' actual ex-post price bids (data), averaged within the sample.



(a) Off Peak (b) Peak

Notes: The graph shows the 95% distribution range of the selected competitor's logged price bids, assumed to follow a normal distribution ($\mu \pm 1.96\sigma$). Firm Index 1-3: Gas Large firms, 4-5: Gas/Oil Mix firms, 6: Other Mix, and 7-8: Heavy Base firms. Firms 1,2,3 and 6 are Large firms and firms 4,5,7, and 8 are medium firms.

Figure 9: Bid range of a competitor with the largest change in belief dispersion: by Firm

sample than in pre-increase sample for most of the strategic firms, extending beyond the belief range of the pre-increase sample, though the extent of the increase in dispersion varies across firms and the range of hours.

Lastly, I examine how firms' bidding patterns differ between the pre- and post-increase samples when they face competitors exhibiting the largest increase in belief dispersion ($\Delta\hat{\sigma}$), compared to when they do not. I assign (t, h) markets to the treatment group by setting $\text{Competitor}_{i,th} = 1$ if the competitor with the highest parameter change appears as a close competitor of firm i in the ex-ante similar market $(\bar{t}, \bar{h})$ used in the estimation.

I estimate the following specification,

$$\begin{aligned} b_{ijth} - mc_{ijt} = \alpha + \beta\ \text{Post-increase}_t + \rho\ \text{Competitor}_{i,th} + \delta\ \text{Post-increase}_t \times \text{Competitor}_{i,th} \\ + \gamma\ \text{Demand}_{th} + \eta + \varepsilon_{ijth} \end{aligned} \tag{9}$$

using the same control variables as in the main specification except the Competitor_{th} variable. Results are presented in Table 11, where I find that firms bid higher in markets where they expect to face competitors whose strategies they have become more uncertain about. Since these competitors are selected based on the change in $\hat{\sigma}$ between the pre- and post-increase samples, the increased dispersion in beliefs in the post-increase sample appears to be associated with firms' bidding behavior, as indicated by a positive and significant coefficient on $\hat{\delta}$. Notably, bids in the pre-increase sample – when facing the same competitor – do not show a significant change (as reflected in $\hat{\rho}$), while they increase in the post-increase sample when facing that competitor.

Firm-level regressions of equation (9), reported in Table A6 in the Appendix, reveal bid response patterns consistent with the changes in parameter estimates, although these patterns are more heterogeneous across firms. Across all firm types, firms adjust their bids to a greater extent –mostly upward – when facing competitors that they become more uncertain about them in the post-increase sample.

	$b_{ijth} - mc_{ijt}$		
	Full Hours	Off-peak Hours	Peak Hours
Post-increase$_t$ (β)	0.868^{**}	0.386	1.554^{***}
	(0.359)	(0.257)	(0.456)
Competitor$_{th}$ (ρ)	0.146	0.01	0.489
	(0.281)	(0.232)	(0.734)
Post-increase$_t$ $\times$ Competitor$_{th}$ (δ)	1.409^{***}	0.278	1.904^{*}
	(0.436)	(0.385)	(0.982)
Hour FE	✓	✓	✓
Year FE	✓	✓	✓
Firm FE	✓	✓	✓
N	34,702	16,106	18,596

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors for regression are clustered at the day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Demand variable (demeaned) is also specified in the regression but not reported.

Table 11: Bid markup with a high $\Delta\sigma$ competitor present

However, the hours in which their bids respond, as well as the direction and magnitude of responses, vary across firms depending on the level of uncertainty they face. For example, as shown in Figure 9, Firm 1 faces greater uncertainty over competitors' strategies (measured by the length of the bid range) during peak hours than during off-peak hours, whereas Firm 2 faces greater uncertainty in the off-peak sample. This difference in relative uncertainty is reflected in the bid responses: δ is positive and significant for Firm 1 in the peak sample, while Firm 2's estimate is positive and significant mainly in the off-peak sample. Moreover, the magnitude of bid responses depends on firms' strategic ability – firms with limited strategic capacity (in terms of both size and idle gas-fired capacity) show weaker responses even when uncertainty increases, and some firms respond by lowering their bids when competitor's bids are expected to be higher.

7 Conclusion

Asymmetric price responses to cost changes are a widespread phenomenon documented across many industries and product markets. More broadly, such asymmetry is related to downward price rigidity, an important feature of price dynamics that shapes the aggregate behavior of economic variables. Despite its prevalence and importance, understanding the sources of such asymmetry has been challenging.

In this paper, I document asymmetric price responses to cost changes in a unique empirical setting where all previously studied sources of asymmetry are absent and show that this asymmetry can arise from firms adopting different strategies. I attribute this finding to inherent asymmetries in beliefs and strategies that depend on the direction of cost change. Specifically, a cost decrease leaves firms with a broader set of rationalizable strategies than a cost increase – a claim supported by the analysis of firms' bidding strategies and the structural estimation of underlying beliefs that rationalize ex-post bids. This, in turn, implies that incomplete responses to cost decreases can emerge solely from strategic considerations when uncertainty over competitors' strategies increases. Although this finding relies on specific context and setting, the strategic basis of asymmetric pass-through examined in this paper has broader implications, as strategic interaction among firms is a fundamental force in economics.

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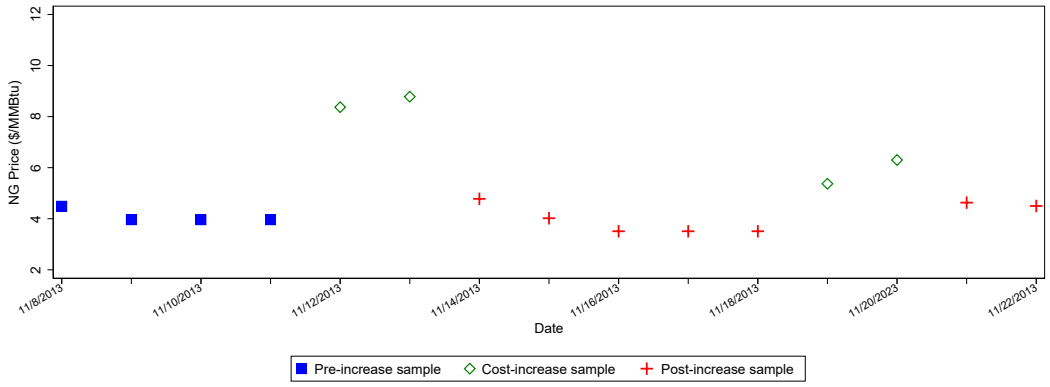
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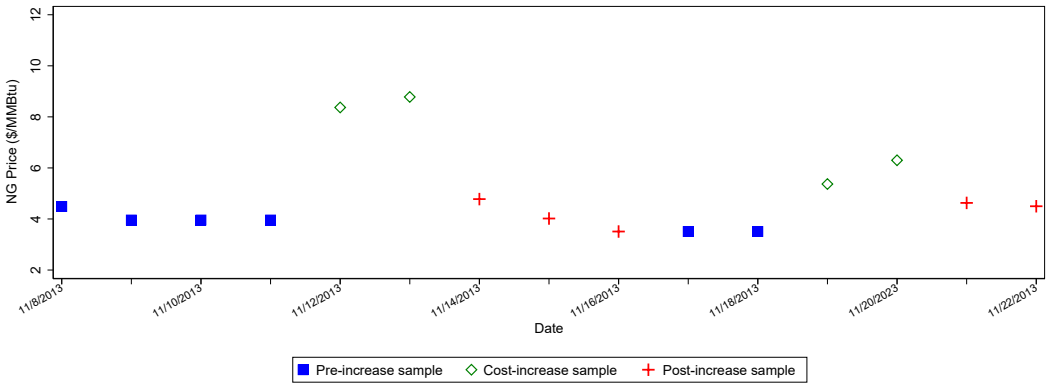
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A Appendix

A.1 Data and Sample



(a) Main Sample Division



(b) Alternative Sample Division

Notes: The figure presents a subset of the dataset, selected to visualize how days are classified into each sample group. Daily natural gas prices are shown together with sample classifications: squares: pre-increase sample; crosses: post-increase sample; diamonds: cost-increase sample. Panel (a) shows the main sample division, and panel (b) shows the alternative sample division.

Figure A1: Visualization of Sample from Data: Main vs. Alternative Categorization

A.1.1 Alternative Pre- and Post-Increase Sample Division

As explained in the robustness check section (Section 3.3.6), I also implemented the analysis with an alternative categorization of the samples by further dividing the post-increase sample days into pre- and post-increase samples. In the main sample division, all base-level gas price days between two cost-increase events were grouped into the post-increase sample. In this new categorization, I reclassified n days before the next cost-increase event, previously part of the post-increase sample, into the pre-increase sample. For example, if a post-increase sample block consists of K days followed by another cost increase event, the main categorization assigned all K days to the post-increase sample. However, because the few days immediately preceding another cost-increase event can be viewed as part of the pre-increase sample, I instead assigned the first n days to the post-increase sample and the remaining $K - n$ days to the pre-increase sample of the subsequent cost increase event. Figure A1 illustrates this comparison between the

main and alternative sample divisions using actual data. The figure displays a subsample of the dataset to clearly show how days are classified into each sample group.

This alternative categorization presents practical challenges. Determining the valid n cannot be done arbitrarily, thus the result of dynamic price pattern analysis implemented in Section 3.3.3 helps identify up to how many days in the post-increase sample exhibit similar price patterns, thus can be grouped into post-increase sample. I find qualitatively similar results when trying $n = 2, 3, 4$, with even stronger results under this alternative categorization, which I discussed in Section 3.3.3. The results for the $n = 4$ case were presented in Columns (5) and (6) of Table 4. While the alternative categorization is feasible and yields qualitatively similar and even stronger results than under the main categorization, I opted for the main categorization due to a relatively short length of the post-increase sample block (average around five days) which implies that the underlying structure of these days within the original block may not differ significantly.

A.1.2 Marginal Cost

The empirical advantage of studying electricity markets is that marginal costs can be directly measured from data, a feature widely utilized in empirical studies. This enables direct assessment of strategic bidding behavior through markups (e.g., Wolfram 1998) and examination of deviations from equilibrium (e.g., Hortaçsu et al. 2019).

A generating unit's marginal cost comprises of its physical efficiency, i.e., heat rate, and the prices of fuel and, when applicable, emissions permits. Some studies use heat rates provided by private data sources (e.g., Hortaçsu and Puller 2008; Hortaçsu et al. 2019) or infer them from CEMS data on generation and fuel use. Structural studies instead estimate marginal costs implied by optimal bidding behavior (Wolak, 2007; Reguant, 2014; Ryan, 2021; Kim, 2022).

I adopt a hybrid approach, using heat rates structurally estimated from an optimal bidding model but computing daily marginal costs by multiplying these rates by observed fuel prices. Using the first-order condition in Equation (6), I estimate heat rates via GMM with the following specification:

$$mc_{ijt} = hr_{ij}(FP_t + \tau e_{ij}) \tag{10}$$

Here, the fuel price, FP_t, and emissions cost τe_{ij} (permit price multiplied by emissions factor) are observable, so estimating marginal cost is equivalent to estimating unit-level heat rates.

For estimation, I use a separate sample with stable gas prices that does not overlap with the main analysis period, particularly the post-increase sample. This estimation sample covers October and March of 2012-2013 (days before the first cost-increase event of the winter season occurs), while the main analysis relies on November-February of years 2012-2014.

This estimation assumes Bayesian Nash Equilibria (BNE) and employs nonparameteric resampling methods that rely on consistent beliefs to approximate the expected bid distribution. Thus, it is important to use a sample without abnormal pricing or bidding behavior. Further details are provided in Kim (2022).

A single heat rate parameter is estimated for each generating unit, representing its physical efficiency, which does not generally vary across days or hours. The daily marginal cost of each unit is then computed using Equation (10) with data on daily fuel prices (Natural Gas Intelligence), emissions permit prices

(Regional Greenhouse Gas Initiative), and emissions factors (EIA).

Although the belief estimation does not impose BNE, using this parameter estimated under the assumption of BNE remains consistent for the following reasons. First, the sample used for estimating the heat rate does not exhibit anomalous pricing or bidding patterns, nor any significant changes in costs, making it valid to assume equilibrium behavior. This sample also does not overlap with the pre- and post-increase samples analyzed in this study. Moreover, since the same heat rate parameter is used in both pre- and post-increase samples, any observed asymmetry is not driven by estimation error in the heat rates. As a measure of physical efficiency, the heat rate parameter is fixed in principle and is not endogenously affected by differences in strategic behavior or beliefs across samples.

A.2 Price Analysis: Additional Robustness Checks

A.2.1 Price Regression Only With the Pre-Increase Sample

To check if the same results will be obtained when using only the days in the pre-increase sample, I implemented a price regression using hypothetical post-increase sample selected from the days in the pre-increase sample. For each day in the original post-increase sample, I selected a most similar day having the closest features regarding the following market variables; daily maximum demand, daily average demand, peak hour maximum and average demand, and gas price levels. Since gas price levels are similar across pre- and post-increase samples, the priority is given to the similarity in demand levels – the maximum and average demand of the peak hours – when selecting similar days. In this way, I have generated counterparts of post-increase sample days among the pre-increase days, and assigned a hypothetical post-increase sample indicator, Hy. Post-Increase$_t$, to this sample. I dropped the original post-increase sample in the analysis. Table A1 shows the results of this first robustness check. Despite

	(1) P_{th}^{da}	(2) log (P_{th}^{da})	(3) P_{th}^{da}
Hy. Post-Increase$_t$	0.376	0.010	0.524
	(0.59)	(0.015)	(0.533)
Peak$_h$			0.824
			(0.541)
Hy. Post-Increase$_t$ × Peak			−0.189
			(0.625)
Hour FE	✓	✓	x
Year FE	✓	✓	✓
N	1,236	1,236	1,236

Notes: Standard errors in parentheses. * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$. Newey-west standard errors with lag $m = 17$. Using only the markets in which the non-dual natural gas units are marginal.

Table A1: Robustness Check: Using Hypothetical Post-Increase Variable

choosing the most similar days of the original post-increase sample among the pre-increase sample, none of the estimates are significantly different from zero. This suggests that the original post-increase sample has some structurally different strategic environment that is not present in the pre-increase sample.

A.2.2 Price Regression with Subsample: Post-increase Days with Lower Gas Prices

The average gas price in the original post-increase sample is slightly higher– by about \$0.2/MMBtu. This minor discrepancy is a natural variation, as data points cannot be identical. Although it does not violate the sample division or weaken the credibility of the analysis, it is important to check whether the main results are sensitive to this difference in average gas prices. To do so, I construct a subsample of the original post-increase sample by selecting days with relatively low gas prices, such that the new post-increase subsample has a lower average gas price than the pre-increase sample. The modified post-increase sample has an average gas price of \$4.17/MMBtu, lower than the average gas price of \$4.29/MMBtu of the pre-increase sample.[51]

	(1) P_{th}^{da}	(2) log (P_{th}^{da})	(3) P_{th}^{da}
Post-Increase$_{t,h}$	1.440**	0.030*	1.309**
	(0.584)	(0.016)	(0.553)
Peak			0.313
			(0.403)
Post-Increase$_{t,h}$ × Peak			0.256
			(0.510)
Hour FE	✓	✓	x
Year FE	✓	✓	✓
N	1,774	1,774	1,774

Notes: Standard errors in parentheses. * $p \leq 0.10$, ** $p \leq 0.05$, ***$p \leq 0.01$. Newey-west standard errors with lag $m = 17$. Using only when the non-dual natural gas units are marginal.

Table A2: Robustness Check: low gas price sub sample of the post-increase sample

If the positive coefficient in the main regression were driven by the slightly higher gas prices in the post-increase sample, the estimated $\hat{\beta}$ from this subsample regression should not be positive and significant. However, Table A2 shows that the coefficient remains positive and significant even when the post-increase sample has lower average gas prices and lower demand. This indicates that the main price regression result is not simply driven by small discrepancies in the market variables.

A.2.3 Pass-through rate estimation

I also estimated a variant of Equation 1 to capture differences in pass-through rates between the pre- and post-increase samples. The challenge with this specification is the limited variation in marginal costs within the sample, which is not ideal for estimating pass-through. Nevertheless, as a robustness check – and because the specification in Equation 11 is more common in the literature – I estimate ρ_1. Results in Table B2 show that the rate is low overall, though higher in the post-increase sample.

$$P_{th} = \beta_0 + \rho_0\, mc_{th} + \ \rho_1 mc_{th}\, D\ + \gamma X_{th} + \mu_h + \eta_t + \varepsilon_{th} \tag{11}$$

[51] Because I selected days to shift the average gas price, demand became slightly more unbalanced across samples, though not substantially. Specifically, the new sample has an average demand of 12,801 MWh, lower than that of pre-increase sample's 13,255 MWh.

Second, I implemented a standard pass-through specification, estimating the rate of price change relative to marginal cost change separately for cost-increasing and cost-decreasing samples, using cost-increase event days instead of using pre- and post-increase samples. Table A9 shows that the estimated rate is lower for the cost-decreasing sample than for the cost-increasing sample, though the sample size is small and this estimation remains subject to the issues discussed in Section 2.1.

A.2.4 Incorporating the cost-increase period information

Throughout the analysis, the cost-increase events served only as an exogenous event used for dividing the samples. Although firms' optimization is largely static, their beliefs and strategies adopted in the post-increase period could be influenced by the characteristics of the cost-increase period.

To assess this, I run a variant of Equation (1) to examine how the price difference across samples is correlated with the magnitude and timing of cost decrease. The first variable, gp_{t-1}, represents the gas price on the last day of each cost-increase event – before the price returned to the post-increase range at time t, which captures the magnitude of the cost decrease. However, in some cases, the gas price declined gradually rather than immediately. For example, as seen in the Event #1 of Figure 2, the price dropped over a couple of rounds before returning to the base level. I define gp_{LastInc} as the gas price on the last day before this decline began and also introduce an indicator, Im_{dec}, to capture whether the return to the base level was immediate.[52] Since these variables are undefined for days before the cost-increase event, the pre-increase sample days are assigned a value of zero for these variables. Therefore, the Post-Increase$t$ indicator is excluded and replaced with the newly generated variables.

Table A3 shows the results. As shown in column (2) regression, a higher gp_{LastInc} is associated with a statistically significant increase in the post-increase sample prices, suggesting that a cost decline from a higher level leads to a more incomplete adjustment of prices. However, $gp_{\text{t-1}}$ has no significant effect, shown in column (1), likely due to limited variation within the sample and the dissipation of effects across multiple rounds of cost declines. Column (3) shows a positive and significant coefficient of Im_{dec}, which indicates that post-increase prices are higher when the cost decrease is immediate rather than spread over several rounds.

	(1)	(2)	(3)	(4)	(5)
			P_{th}		
gp_{t-1}	0.172			-0.00711	
	(0.242)			(0.265)	
gp_{LastInc}		0.108***			0.120***
		(0.0369)			(0.0373)
Im_{dec}			1.467**	1.474***	1.592***
			(0.580)	(0.564)	(0.603)
N	2,833	2,833	2,833	2,833	2,833

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A3: Price regression: with characteristics of the cost-increase period

[52] Pre-increase sample days are assigned $Im_{\text{dec}} = 0$, assuming a sufficiently long gap since the last cost increase.

A.3 Bidding Analysis

A.3.1 Bid distribution change: quartile analysis

An initial examination of the bidding data suggests a change in bidding patterns. I compare the distribution of price bids, b_{ijkth}, between the pre- and post-increase samples, as shown in Figure A2. Price bids of generating units j of the pre-increase sample are ranked in increasing order, and index values from 1 to 4 are assigned to units in each quartile, separately for each demand group (e.g., low to high demand).[53] I then plot the bid distributions of these units for the post-increase sample in increasing order and examine whether their quartile indices match those of the pre-increase sample. Panels (a) and (b) show the distributions for the lowest-demand subsample (e.g., off-peak hours), while panels (c) and (d) correspond to the highest-demand subsample (e.g., peak hours).

If bidding strategies were consistent across the pre- and post-increase samples, the bids in panels (b) and (d) would be expected to align with those in panels (a) and (c). However, the distributions do not preserve their original order: units in the first and second quartiles of the pre-increase sample tend to bid higher, and bids are more dispersed across all quartiles in the post-increase sample. This suggests that the original bid rankings are not preserved – previously low-bidding units no longer bid the lowest, and vice versa. The mixing of quartile groups indicates that firms may be employing different bidding strategies in the post-increase sample.

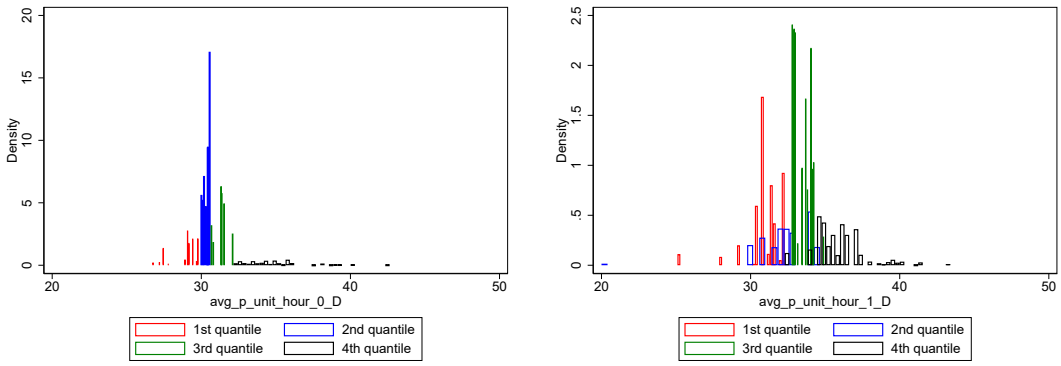
A.3.2 Discussion: other possible causes

Forward contract Electricity-generating firms often set up forward contracts with the demand side (retail companies), which can reduce their responsiveness to wholesale market conditions and limit strategic behavior when forward obligations are binding (see Bushnell, Mansur, and Saravia, 2008). One might question whether the documented differences between samples could result from forward contracts. However, this can be ruled out, as forward contract terms should be the same for sample days that differ only in cost direction. Firm-level forward contract rates are typically fixed for at least a season and do not change over short periods. Since the pre- and post-increase samples in our analysis are at most a month apart, the forward contract rate can be assumed constant.[54]

Fixed costs Another factor is the fixed cost of power plant operation, such as start-up or ramping costs. Power plants incur an initial fixed cost when starting or additional costs when ramping up. These fixed costs can introduce dynamic considerations into production decisions. However, if these costs exist, they are present in both pre- and post-increase periods, not specific to either sample. Moreover, these costs typically create dynamic linkages in production across hours, but not across days. Given that the price asymmetry I observe is mainly across days in different samples, it cannot be explained by fixed costs. Finally, fixed start-up costs are typically relevant for conventional baseload generators, such as

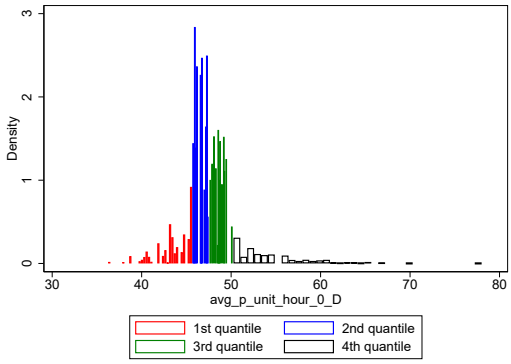
[53] I also tried an alternative method of using the price bid of a single closest-to-marginal step bid of each unit j instead of the volume-weighted bids, where I find qualitatively similar graphs.

[54] Using the rate instead of the actual amount of forward contracts is not an issue. Even if the rates are proportional to production, total hourly output remains nearly the same in both samples after controlling for marginal cost, demand, and other market conditions.

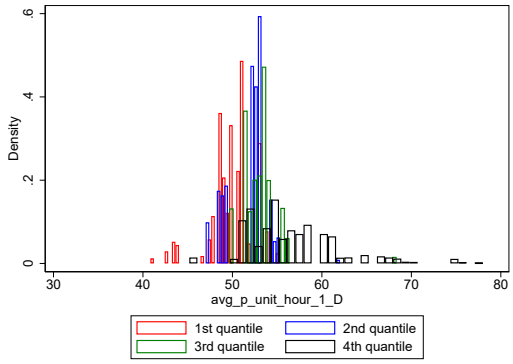


(a) Pre-increase: Low Demand (gr 1)

(b) Post-increase: Low Demand (gr 1)



(c) Pre-increase: High Demand (gr 4)



(d) Post-increase: High Demand (gr 4)

Figure A2: Distribution of (volume-weighted) price bids of pre- and post-increase samples: by demand

nuclear or coal, but not for gas-fired generators. Because my analysis focuses on marginal cost changes to gas-fired generators, fixed costs are not a concern and cannot account for the observed asymmetry.

A.4 Model

A.4.1 Equilibrium Concept

Determining whether the observed behaviors are better explained by an equilibrium or a non-equilibrium model would require additional testing and model comparison, similar to the approach in Hortaçsu et al. (2019). In their setting, off-equilibrium behavior by small firms could be clearly identified, making it evident that a standard Bayesian Nash Equilibrium (BNE) model could not explain all observed outcomes.[55] In contrast, such identification is much more difficult in my setting. It is not straightforward to falsify or rule out the possibility that the observed outcome reflects one of multiple equilibria. Thus, even testing whether an observation is on- or off-equilibrium is inherently challenging. As a result, model selection – determining which framework best fits the data – is complicated by the lack of clear predictions from either class of models, especially when multiple equilibria cannot be excluded. Moreover, even if one wishes to compare an equilibrium model with a non-equilibrium model, the choice of which

[55]Moreover, the analyses in Hortaçsu and Puller (2008) and Hortaçsu et al. (2019) were feasible in part because the model imposed a specific structure: uncertainty entered only through the forward contract, which induced a single equilibrium path characterized by parallel shifts in bidding strategies. The model I adopt differs from theirs in that I allow uncertainty to arise from changes in the residual demand slope.

non-equilibrium framework to use is non-trivial. For example, the level-k model used in Hortaçsu et al. (2019) requires identifying a type-0 (non-strategic) player, but in my context, it is not obvious which firm – or what behavior – should be classified as less sophisticated. Similarly, models based on fictitious play (as in Doraszelski et al. (2018)) rely on players forming beliefs based on past play, but in this setting, firms make decisions that cannot be rationalized as responses to observable past competitor behavior.

A.4.2 Why not dynamic decision-making?

The strategic interaction in this market is not dynamic in the sense that there is no dynamic feed loop between actions and state variables, though there is a dynamic element in terms of the belief formation.

The strategic interaction in this market is not dynamic in the conventional sense, as there is no feedback loop between firms' actions and state variables. Firms aim to maximize static payoffs (profits), which are realized each period and depend solely on contemporaneous state variables. These state variables – such as gas prices and demand – are exogenously determined, with transition probabilities given by $f(X_{t+1})$ rather than $f(X_{t+1}|Y_t, X_t)$, since both gas prices and demand are driven by weather and residential consumption behavior, factors outside the model. Consequently, X_t is stochastic, and firms have no incentive to choose actions today to influence competitors' behavior in future periods.

The game is simultaneous rather than sequential, and it is not a repeated game, as market fundamentals X_t change stochastically each period. Unlike standard dynamic games, where current actions depend on past states, actions, or observed outcomes, and players incorporate historical fundamentals into current decisions, the present setting lacks such dynamics in fundamentals. Instead, the intertemporal element arises solely through the evolution of beliefs. Specifically, firms' beliefs about competitors' strategies today, denoted $B_{i,t}$, depend on the current state variable X_t, an error term ε_t, and the direction of cost change $d_t = \text{sgn}(g_t - g_{t-1})$, where $(g_t - g_{t-1})$ is exogenously determined. In this sense, the setting retains a limited dynamic feature through belief updating, as past state variables – particularly the gas price level g_{t-1} – influence firms' expectations and perceived strategies of competitors in the current period.

A.5 Estimation

A.5.1 Estimation Method

Expectation Approximation The expectation terms that appear in Equation (8) are approximated as follows:

$$E_{-ith}\left[RD'(\widetilde{\mathbf{b}}_{-ith})\right] = \prod_{m=1}^{M}\int_0^\infty RD'(\widetilde{\mathbf{b}}_{-ith})\,\phi_{i,m}(b_{i,m})\,db_{i,m} \approx \frac{1}{S}\sum_{s=1}^{S} RD'(\widetilde{\mathbf{b}}^s_{-ith})$$

$$E_{-ith}\left[Q_{ith}(\widetilde{\mathbf{b}}_{-ith})\right] = \prod_{m=1}^{M}\int_0^\infty Q_{ith}(\widetilde{\mathbf{b}}_{-ith})\,\phi_{i,m}(b_{i,m})\,db_{i,m} \approx \frac{1}{S}\sum_{s=1}^{S} Q_{ith}(\widetilde{\mathbf{b}}^s_{-ith})$$

where $\phi_{i,m}(\cdot)$ denotes firm i's belief distribution of competitor m's bids $b_{i,m}$. I use $S = 500$ draws to construct these simulated expectation terms.

A.5.2 Competitor summary

Table A4 shows the competing units summarized by their firm type. In summarizing I grouped firm i into four types, using the same category as for the firms of competing units. Overall, the Gas Large firm types most frequently appear as competitors of most type of firms. Table A5, which is a summary by peak and off-peak hours, shows that the relative share of Gas Large type competitors is lower in the peak hours than in the off-peak hours, and increasingly more of mixed type firms (both gas/oil and base/gas) become competitors during peak hours, indicating that firms are slightly more likely to face the Gas Large firm type as a competitor in the off-peak hours.

	Competing Firm Type (share)			
Firm Type	Heavy Base	Gas Large	Gas/Oil Mix	Base/Gas Mix
Heavy Base	0.08	0.49	0.17	0.11
Gas Large	0.12	0.43	0.18	0.11
Oil/Gas Mix	0.12	0.48	0.14	0.11
Base/Gas Mix	0.12	0.48	0.17	0.07
Total	0.11	0.47	0.16	0.10

Table A4: Competitor Firm Type Share: Total

	Competing Firm Type (share)			
Firm Type	Heavy Base	Gas Large	Gas/Oil Mix	Base/Gas Mix
	Off-Peak Hours			
Heavy Base	0.08	0.55	0.14	0.08
Gas Large	0.12	0.48	0.14	0.08
Oil/Gas Mix	0.11	0.54	0.11	0.08
Base/Gas Mix	0.11	0.54	0.13	0.05
Total	0.11	0.53	0.13	0.08
	Peak Hours			
Heavy Base	0.08	0.46	0.19	0.12
Gas Large	0.13	0.40	0.19	0.12
Oil/Gas Mix	0.12	0.45	0.16	0.12
Base/Gas Mix	0.12	0.45	0.19	0.09
Total	0.12	0.44	0.18	0.12

Table A5: Competitor Firm Type Share: Off-Peak and Peak Hours

A.5.3 Moment condition and Estimation

Since the dimension of the moment vector corresponds to the number of hours (H) in which the bids of parameterized competitors appear, the total number of estimable parameters from this moment condition does not exceed H. Note that H and the number of days (T) vary across firms and samples, as they depend on the number of markets in which the parameterized competitors are observed.

One caveat of the estimation is that I pool days and hours within each sample to estimate a single set of parameters per competitor. This implies that if beliefs vary across (t, h) within the sample, the estimated parameters will reflect the average of those belief distributions. As shown in Section 3.3.3, prices in the post-increase period exhibit a slight decreasing path over time, suggesting that beliefs could be adjusted. While estimating at the daily level would be ideal, doing so would sacrifice sufficient variation in

competitor sets within each firm, which is critical for identification. Therefore, the parameters estimated from the pooled data can be interpreted as the average beliefs that rationalize the observed price patterns within the post-increase sample.

A.6 Tables and Figures

	$b_{ijth} - mc_{ijt}$							
Firm Type:	Gas Large			Gas/Oil Mix		Other Mix	Heavy Base	
Firm Size:	Large			Medium		Large	Medium	
Firm (Index)	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5	Firm 6	Firm 7	Firm 8
$\hat{\delta}$								
Full	2.272^{***}	1.178^{**}	0.373	-1.952	-1.977	1.251	1.787^{**}	4.151^{***}
	(0.576)	(0.501)	(0.630)	(1.412)	(2.436)	(1.081)	(0.899)	(0.985)
Off peak	0.544	0.912^{**}	-0.496	1.374	-1.098	0.299	-1.297^{*}	2.151
	(0.576)	(0.449)	(0.784)	(1.225)	(2.544)	(0.922)	(0.766)	(2.188)
Peak	3.684^{***}	2.457	1.725^{**}	-6.677^{***}	-2.530	2.719^{*}	5.523^{***}	2.930^{*}
	(1.376)	(2.935)	(0.772)	(1.587)	(3.247)	(1.522)	(2.060)	(1.717)
$\hat{\rho}$								
Full	-1.041^{**}	-0.063	0.475	1.793^{*}	-1.052	0.356	-1.337^{**}	1.297^{**}
	(0.423)	(0.365)	(0.526)	(1.039)	(1.915)	(0.543)	(0.649)	(0.524)
Off peak	-0.281	-0.076	0.732	-1.063	-1.031	0.718	-0.043	0.266
	(0.326)	(0.317)	(0.551)	(1.054)	(1.939)	(0.561)	(0.538)	(0.619)
Peak	-0.784	-0.436	-1.242^{**}	3.191^{**}	-1.137	-0.506	-3.081^{**}	2.619^{**}
	(1.120)	(2.733)	(0.540)	(1.538)	(1.834)	(0.633)	(1.258)	(1.304)

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors for regression are clustered at the day (t) level. Hour and Year fixed effects are included. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. For Firm 2, the most peak hours (16-22h) among the original peak-hour category were used. Unit fixed effect is specified for Firm 6 due to its large number of generating units in the sample.

Table A6: Firm-level Regression: Bid Markup with a high $\Delta\sigma$ competitor present

	mean	med	min	max	s.d.	N
Block's maximum k	5.05	4	1	10	2.99	19

Notes: Each block within the phase 2 have multiple days which I indexed by k. The table shows the summary of the block-level maximum k.

Table A7: Summary statistics of maximum of block-level day index, k

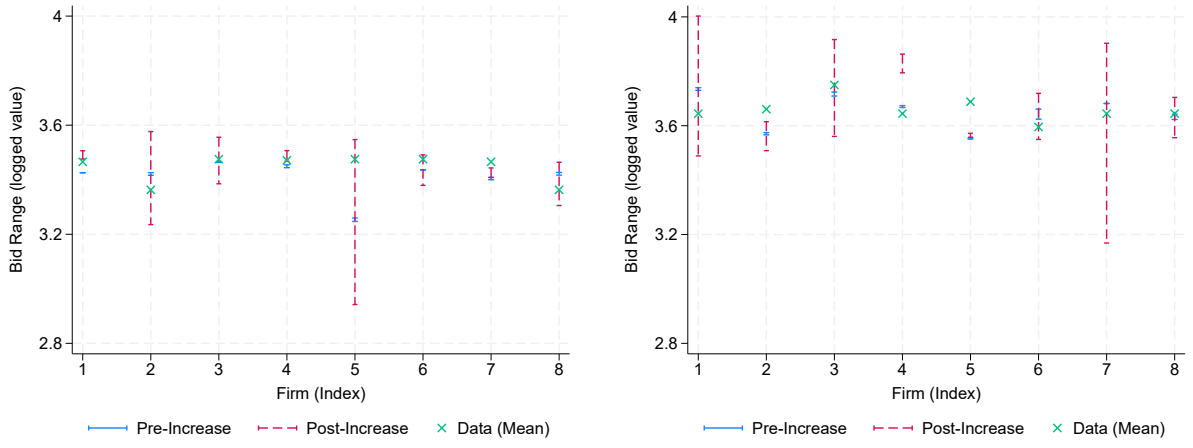
Adjustment	Variable	Sample	Mean	Median	S.D.	min	max	Obs
a. Sample Matched	gas price	pre-	4.44	4.49	0.26	4	5.18	173
		post-	4.43	4.50	0.29	4.02	5.16	313
c. Sample Matched + first day dropped	gas price	pre-	4.44	4.49	0.27	4	5.18	173
		post-	4.39	4.41	0.27	4.02	5.16	253
a. Sample Matched	demand	pre-	13550	14033	3446	6617	21505	173
		post-	13260	13511	2955	6529	21113	313
c. Sample Matched + first day dropped	demand	pre-	13550	14033	3446	6617	21505	173
		post	13133	13367	3012	6648	20583	253

Table A8: Summary Statistics: Robustness Checks

	(1) $P_{t,h}$ (Inc)	(2) $P_{t,h}$ (Dec)
MC (implied cost)	1.096	0.997
	(0.069)	(0.025)
Month FE	✓	✓
Daytime FE	✓	✓
Hour FE	✓	✓
N	841	685

Notes: Standard errors in parentheses. Using only the sample when natural gas prices rise above the normal level (shock period). The sample consists of days when non-dual natural gas generating units are marginal. *Inc* sample includes days when natural gas price is in an increasing path and *Dec* sample includes days when the natural gas price is in a decreasing path. The marginal cost is instrumented with gas spot price.

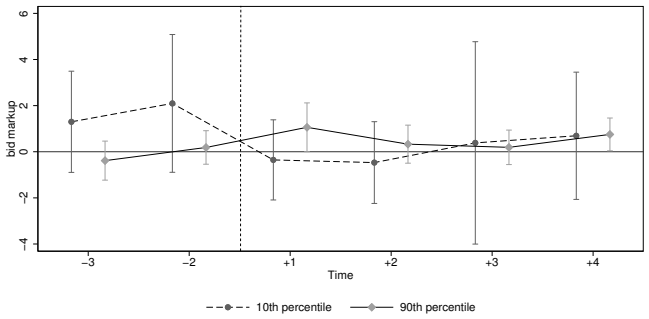
Table A9: Pass-through: increasing and decreasing sample, IV regression



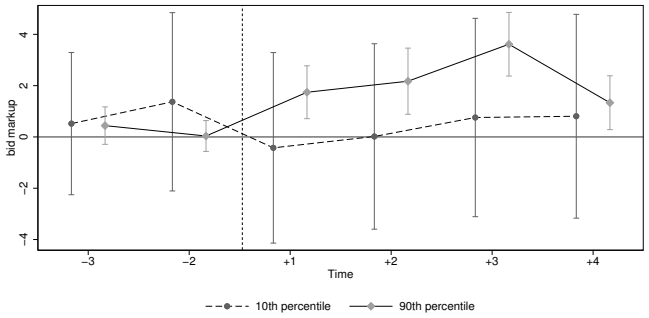
(a) Off Peak (b) Peak

Notes: Firm Index 1-3: Gas Large firms, 4-5: Gas/Oil Mix firms, 6: Other Mix, and 7-8: Heavy Base firms. Firms 1,2,3 and 6 are Large firms and firms 4,5,7, and 8 are medium firms. "Data" shows the mean of the competitor's ex-post bids.

Figure A3: Bid range of a competitor with the largest change in belief dispersion: by Firm, with mean price bid



(a) Off-Peak Hours



(b) Peak Hours

Notes: The graph shows the estimated bid markup difference ($\hat{\beta}_{1,k}$) for 10th and 90th percentiles for each period ($Time$) $k = \{-3, -2, +1, +2, +3, +4\}$, relative to the baseline comparison period $k = -1$. Time $k < 0$ is part of the pre-increase sample, and $k > 0$ is part of the post-increase sample. Panel (a) shows the off-peak hours, and Panel (b) shows peak hours. Confidence intervals are computed using standard errors clustered at generating unit level (5% significance level).

Figure A4: Bid markup dynamics: Off-peak and Peak hours

Online Appendix

B.1 Model

B.1.1 Smoothed supply bid, residual demand, and weight

The derivatives of the supply offer curve and the residual demand curve of each firm enter the empirical analogue of the first-order condition. Since these curves are submitted as step functions, I first smooth the curves using the normal kernel smoothing approach following Wolak (2007), using a bandwidth of \$3/MWh for the Sample 0 estimations and \$6/MWh for the Sample 1 estimations. As a robustness check, I tried different bandwidths to see how sensitive the derivatives are to the bandwidth selection. Results are quite robust across bandwidths except for some days when electricity prices are extremely high.

Let firm i's unit j's step k bid to be $\mathrm{b}_{ijkht} =< b_{ijkht}, q_{ijkht} >$. Suppose the market clearing price at hour h is P_{ht}. Note that $\mathcal{K}$ and κ are the CDF and pdf of a normal distribution. Then, the smoothed supply bid curve of firm i using the bandwidth bw is represented as below:

$$\widehat{Q}_{iht}\left(P_{ht}, \mathbf{b}_{iht}\right) = \sum_{j \in J_i} \sum_{k} q_{ijkht}\, \mathcal{K}\Big(\frac{P_{ht} - b_{ijkht}}{bw}\Big)$$

The smoothed residual demand curve of firm i, using bandwidth bw is shown below:

$$\widehat{RD}_{iht}\left(P_{ht}, \mathbf{b}_{-iht}\right) = D_{ht} \; - \sum_{m \neq i} \sum_{j \in J_m} \sum_{k} q_{mjkht}\, \mathcal{K}\Big(\frac{P_{ht} - b_{mjkht}}{bw}\Big)$$

Then the derivative of the residual demand curve is:

$$\frac{\partial \widehat{RD}_{iht}}{\partial P_{ht}}\left(P_{ht}, \mathbf{b}_{-iht}\right) = -\frac{1}{bw} \sum_{m \neq i} \sum_{j \in J_m} \sum_{k} q_{mjkht}\, \kappa\Big(\frac{P_{ht} - b_{mjkht}}{bw}\Big)$$

Finally, the expression of the weight, which is the probability of bid step b_{ijkht} being the marginal unit, is shown below (Wolak, 2007):

$$\frac{\partial P_{ht}}{\partial b_{ijkht}} = \frac{\partial \widehat{Q}_{iht}(P_{ht})}{\partial b_{ijkht}} \Big/ \Big(\frac{\partial \widehat{RD}_{iht}(P_{ht})}{\partial P_{ht}} - \frac{\partial \widehat{Q}_{iht}(P_{ht})}{\partial P_{ht}}\Big)$$

B.1.2 Ex-ante expectation and ex-post realizations

As a preliminary check before estimating beliefs, I computed the bid markup using the *ex post* optimal bid – what would have been optimal if the firm had known ex ante uncertain information about $\mathbf{b}_{-it}$, following Doraszelski et al. (2018). Specifically, I calculate the bid markup using equation (7), substituting realized competitors bids $\mathbf{b}^*_{-it}$, which firms do not observe at the time of bidding. Thus, the ex post bid markup serves as an upper bound on the value of information acquisition (Doraszelski et al., 2018). [56]

The ex post bid markup, bidmarkup^*_{ith}, differs from the observed bid markup, $[b_{ijkht} - mc_{ijt}]^{obs}$. The difference reflects how firms' expected bid distributions deviate from the perfect information case,

[56] Since firms correctly observe the bid distribution, this calculation assumes no uncertainty.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Sub Sample: by Firm Type					
		med	large	Heavybase	Gaslarge	Gas/oil mix	Other Mix
		$\mathbf{1}(\Delta\text{bidmarkup})$					
Pre-Increase							
Peak_h	0.038	-0.074^{**}	0.063^{**}	-0.071^{**}	0.098^{***}	-0.024	0.056^{*}
	(0.037)	(0.027)	(0.025)	(0.029)	(0.033)	(0.020)	(0.032)
constant	0.265^{***}	0.257^{***}	0.253^{***}	0.171^{***}	0.282^{***}	0.150^{***}	0.227^{***}
	(0.048)	(0.030)	(0.020)	(0.034)	(0.022)	(0.022)	(0.032)
Post-Increase							
Peak_h	-0.003	0.001	-0.004	0.003	0.008	-0.003	0.037
	(0.022)	(0.021)	(0.017)	(0.023)	(0.019)	(0.020)	(0.033)
constant	0.268^{***}	0.111^{***}	0.292^{***}	0.073^{***}	0.291^{***}	0.116^{***}	0.323^{***}
	(0.025)	(0.017)	(0.017)	(0.016)	(0.018)	(0.020)	(0.037)
Hour FE	x	x	x	x	x	x	x
Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
N (Pre-Increase)	15,074	2,588	12,370	2,150	7,807	1,734	3,251
N (Post-Increase)	15,979	2,752	13,129	2,458	9,198	1,208	3,013

Notes: Standard errors in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$. Standard errors for regression (1) are clustered at the day (t) and firm (i) level, and standards errors for the subsample regressions (2)-(5) are clustered at day (t) level. Day-hour (th) samples only when the non-dual natural gas generators set the price (i.e. marginal) are used for estimation. Generating units with positive marginal probability (ex post) included in the sample. Demand variable (demeaned within each firm group and sample, unit is MWh) is also specified in the regression but not reported.

Table B1: Probability of occurence of ex-post, ex-ante bidmarkup difference

on average.[57] I examine the sign of this markup difference to assess whether firms perceived residual demand as more inelastic or elastic relative to the ex post bid distribution. A positive difference suggests the firms expected weaker competition – implying relatively inelastic residual demand – and the negative is for the opposite. Comparing markup differences across the Pre-Increase and Post-Increase samples allows us to assess whether firms' belief sets differ, using the ex post optimal level as a reference.

Table B1 presents the probability of a positive bid markup difference, analyzed separately for the pre- and post-increase samples. Using the dependent variable $\mathbf{1}(\Delta\text{bidmarkup}_{ith})$, this regression captures the likelihood of a positive bidmarkup difference and how it varies between peak and off-peak hours.[58] I estimate this separately for the pre- and post-increase samples to explore cross-hour patterns within each sample.

While the overall estimates are nearly identical between samples (column 1) differences emerge across firm types. When grouped by size (columns 2-3), medium-sized firms show a lower probability of a positive difference in peak hours in the pre-increase sample, suggesting they perceived stronger competition in peak hours. On the other hand, large firms exhibit a higher probability, implying they perceived residual

[57] Since firms maximize ex ante expected profits, their actual bids may not be ex post optimal. The difference between ex ante and ex post implied bid markups, often called ex post regret, serves as an upper bound on markup adjustments due to information acquisition (Doraszelski et al., 2018; Hortaçsu and Puller, 2008).

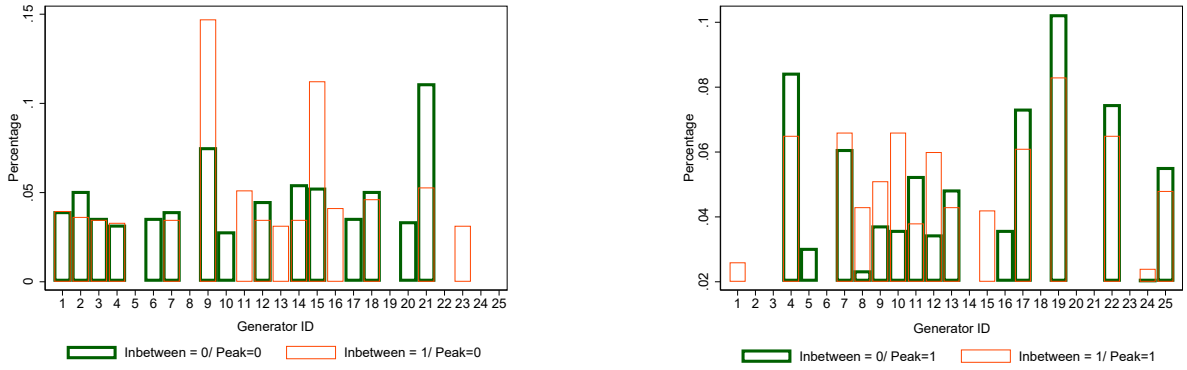
[58] A linear probability model is preferable here since the main independent variable is a binary indicator, making probit and logit estimations less suitable.

demand more inelastic in peak hours. However, these patterns disappear in the post-increase sample. Columns (4)-(7) report results by firm characteristics. In the pre-increase sample, Gas Large and Other Mixed firms have larger coefficients for peak hours, indicating they perceived more inelastic demand in peak hours – consistent with their typical bidding patterns. Conversely, heavy base firms show lower coefficients, suggesting they perceived to have faced more elastic residual demand in peak hours, likely due to owning fewer strategic peak-hour assets. In the post-increase sample, these distinct peak vs. off-peak patterns disappear across all groups, with no significant differences in occurrence probabilities. This aligns with findings from the bidding pattern analysis, suggesting that firms' average perceptions of competitors' bid distributions (residual demand) become more evened out across hours in the post-increase period.

B.2 Tables and Figures

	$P_{t,h}$
MC × Post-Increase	0.105**
	(0.043)
Post-Increase	-1.102
	(1.721)
MC	0.105***
	(0.034)
Hour FE	✓
Year FE	✓
N	2,833

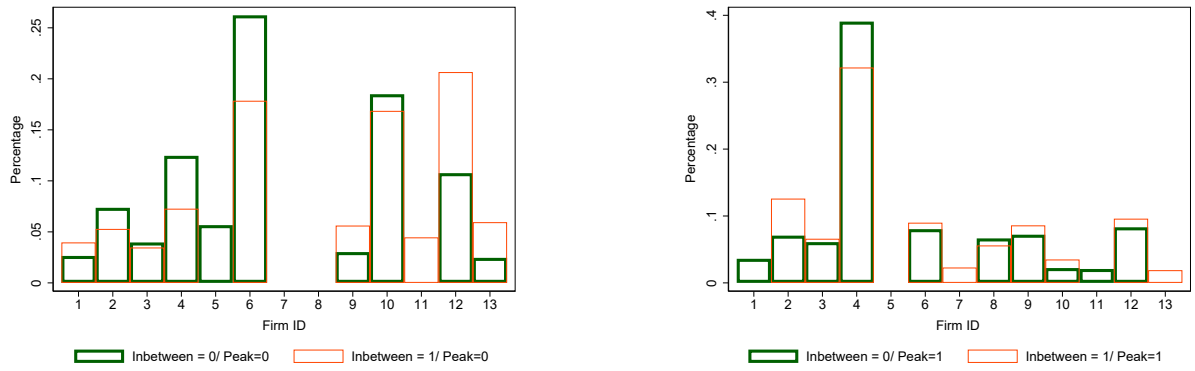
Table B2: Pass-through difference: Pre- and Post-Increase Samples



(a) Offpeak Hours (b) Peak Hours

Notes: The graph shows the percentage of each unit's occurrences as marginal power plant, taken separately by Pre-increase and Post-increase samples and Peak and Off-peak samples. Generation ID indicates an arbitrary index assigned to each generating unit. Figure B1 was generated by assigning unique IDs to ex-post marginal units and plotting their percentage occurrences as marginal units in the pre- and post-increase samples. These graphs were created separately of off-peak and peak hours, and in both cases, we observe shifts in the composition of marginal price setters. A similar analysis at the firm level, shown in Figure B2 in the Online Appendix, indicates composition changes, though they are less pronounced than at the unit level.

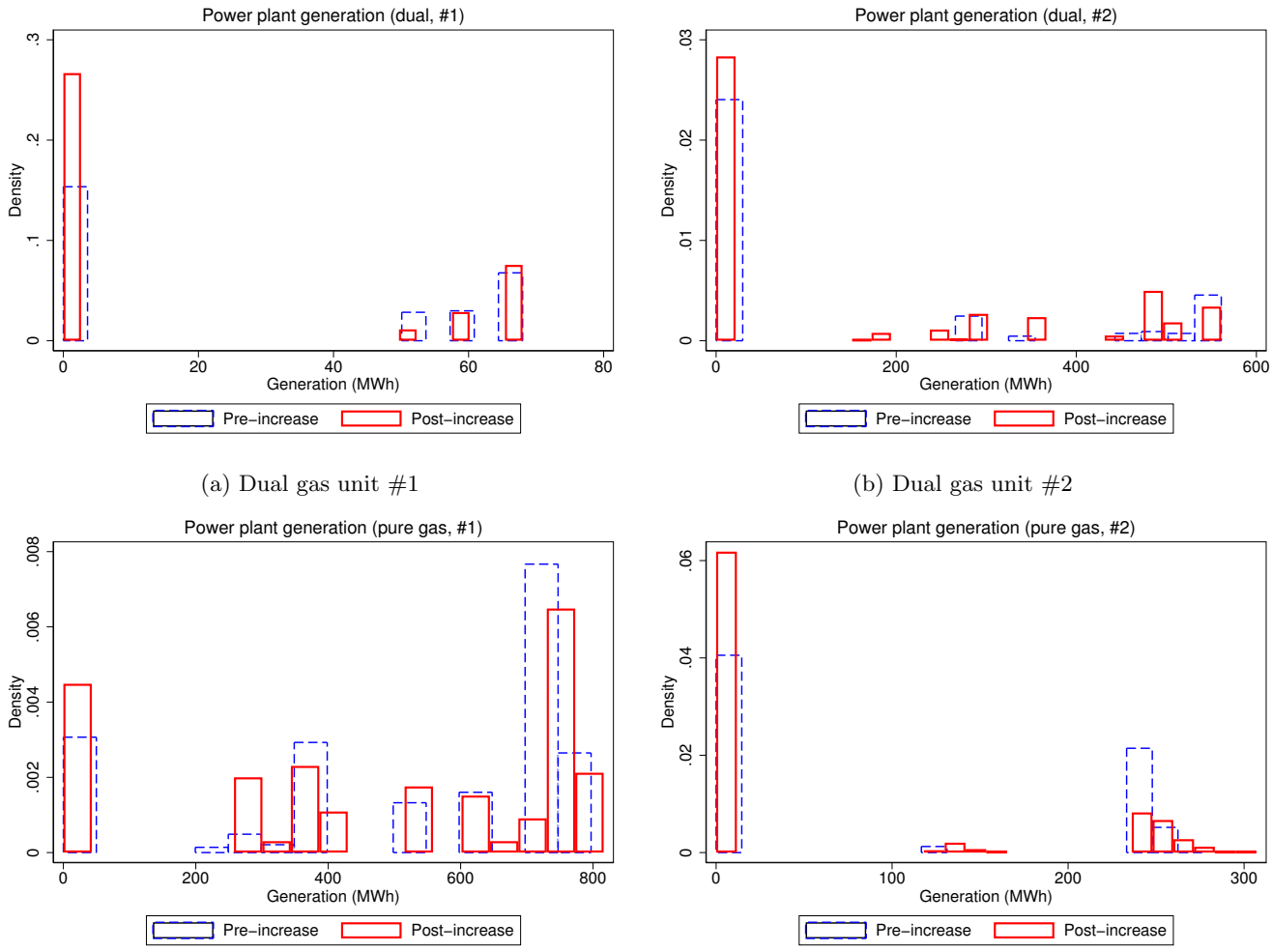
Figure B1: Marginal Units: distribution by Pre- and Post-Increase and Peak/Offpeak



(a) Offpeak Hours (b) Peak Hours

Notes: The graph shows the percentage of each firm's occurrences as being a marginal price setter (by owning the marginal power plant), taken separately by Pre- and Post-increase samples and Peak and Off-peak samples. Firm ID indicates an arbitrary index assigned to each firm.

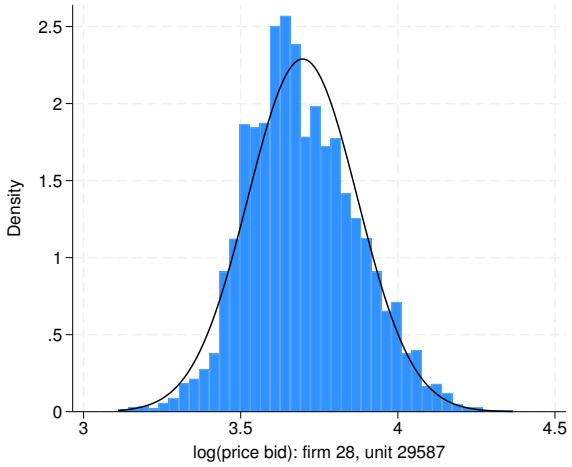
Figure B2: Marginal Firms: distribution by Pre- and Post-Increase and Peak/Off-peak



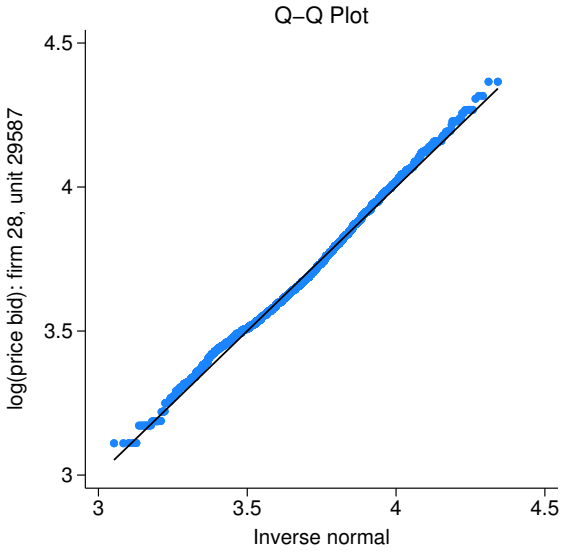
(a) Dual gas unit #1 (b) Dual gas unit #2

(c) Gas unit #1 (d) Gas unit #2

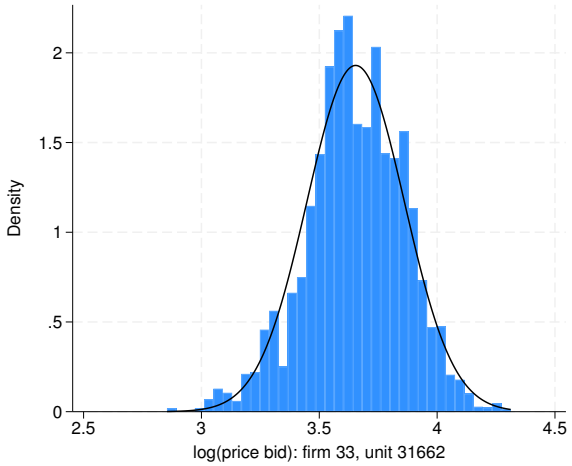
Figure B3: Histogram of generator-level quantity: pre-increase vs. post-increase



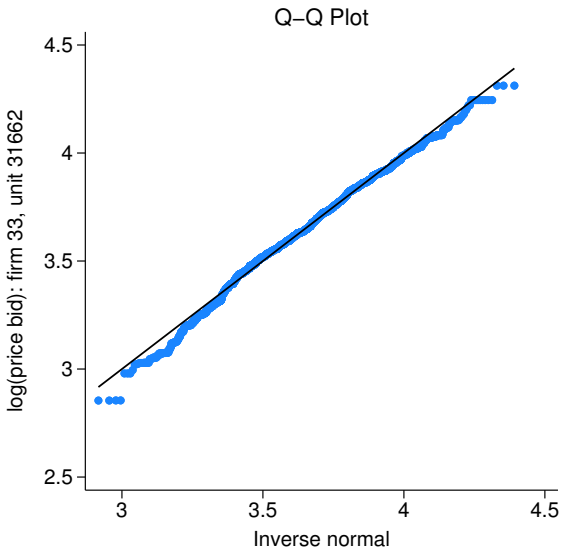
(a) Firm 28: distribution



(b) Firm 28: Q-Q plot



(c) Firm 33: distribution



(d) Firm 33: Q-Q plot

Figure B4: Log transformed Price Bids: single generating unit's of firm 28 and 33